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International Financial Markets and Monetary Policy

Edited by
Robert Czudaj

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International Financial Markets and Monetary Policy

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Editor

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About the Editor

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Preface to "International Financial Markets and Monetary Policy"

The global financial crisis plunged the global economy into a great recession. Many central banks responded with unconventional monetary policies such as quantitative easing, negative policy rates, and forward guidance to calm down financial markets. The COVID-19 pandemic led the global economy, financial markets, and central banks to face even more severe problems. Central banks set up further asset purchase programmes to complement existing unconventional monetary policy measures that have already been in place to help the economy to absorb the COVID-19 shock. The new crisis has increased the importance of preserving financial stability through the international cooperation of central banks around the globe. Managing the expectations of market participants plays a crucial role in the context of financial stability. Therefore, the aim of this Special Issue is to disseminate important empirical and theoretical research questions concerning the connection between monetary policy and international financial markets and to stimulate discussion among academics and policymakers. A special focus is devoted to emerging and developing economies.

The Special Issue covers several different articles on a variety of topics from the fields of monetary policy and international financial markets. The contributions address research questions on exchange rates, cryptocurrencies, stock markets, the connection between money supply and inflation after the COVID-19 pandemic, the role of commodity price shocks for banking system stability in developing countries, global liquidity effects, the twin deficit, and the Taylor rule.

Robert Czudaj

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Article

Application of Taylor Rule Fundamentals in Forecasting Exchange Rates

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Abstract: This paper examines the effectiveness of the Taylor rule in contemporary times by investigating the exchange rate forecastability of selected four Organisation for Economic Co-operation and Development (OECD) member countries vis-à-vis the U.S. It employs various Taylor rule models with a non-drift random walk using monthly data from 1995 to 2019. The efficacy of the model is demonstrated by analyzing the pre- and post-financial crisis periods for forecasting exchange rates. The out-of-sample forecast results reveal that the best performing model is the symmetric model with no interest rate smoothing, heterogeneous coefficients and a constant. In particular, the results show that for the pre-financial crisis period, the Taylor rule was effective. However, the post-financial crisis period shows that the Taylor rule is ineffective in forecasting exchange rates. In addition, the sensitivity analysis suggests that a small window size outperforms a larger window size.

Keywords: Taylor rule fundamentals; exchange rate; out-of-sample; forecast; random walk; directional accuracy; financial crisis

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1. Introduction

Exchange rates have been a prime concern of the central banks, financial services firms and governments because they control the movements of the markets. They are also said to be a determinant of a country's fundamentals. This makes it imperative to forecast exchange rates. Generally, one could ask, is there any benefit in accurately forecasting the exchange rates? Ideally, there is no intrinsic benefit to accurate forecasts; they are made to enhance the resulting decision making of policymakers (Hendry et al. 2019).

One of the popular investigations into the exchange rate movements was made by Meese and Rogoff (1983). In their paper, they perform the out-of-sample exchange rates forecast during the post-Bretton Woods era. They found that the random walk model performs better with the exchange rate forecast than the economic fundamentals. This was the Meese–Rogoff puzzle. Subsequently, researchers have challenged the Meese and Rogoff findings. Mark (1995) uses the fundamental values to show the long-run predictability of the exchange rate. Clarida and Taylor (1997) use the interest rate differential to forecast spot exchange rates. Mark and Sul (2001) also find evidence of predictability for 13 out of 18 exchange rates using the monetary models.

In 1993, John B. Taylor presented monetary policy rules that describe the interest rate decisions of the Federal Reserve's Federal Open Market Committee (FOMC). In most literature, this has been named the Taylor rule. Taylor (1993) stipulates that the central bank regulates the short-run interest rate in response to changes in the inflation rate and the output gap (interest rate reaction function). This has become a monetary policy rule which the Federal Reserve (Fed) and other central banks have incorporated into their decision making (Taylor 2018). The Taylor rule principle is used in this study due to its effectiveness in monetary policy. It is superior to the traditional models as it combines the uncovered interest rate parity, the purchasing power parity and the other monetary variables for forecasting exchange rates. This makes it a more robust method for forecasting the exchange rates. The Taylor rule monetary policy operates well in countries that practice floating exchange rates with an inflation-targeting framework.

Economists have derived two versions of the Taylor rule to forecast the exchange rate. These include Taylor rule differentials and Taylor rule fundamentals. Engel et al. (2008) developed the Taylor rule differentials model by subtracting the Taylor rule of the domestic country from that of the foreign country. Instead of using the estimated parameters, they apply the postulated parameters into the forecasting regression to perform the test. They perform out-of-sample predictability of the exchange rate and find that the Taylor rule differentials models perform better than the random walk in the long horizon compared to the short horizon. Other literature including Engel et al. (2009) provides supporting evidence of the Taylor rule models in predicting the exchange rate.

The Taylor rule fundamentals model was first established by Molodtsova and Papell (2009). They deducted the Taylor rule of the foreign country from the domestic country and the variables contained in the Taylor rule equation are directly utilized to perform an out-of-sample prediction for the exchange rate. Rossi (2013) surveys the exchange rate forecast models in most literature and finds strong evidence in favor of the Taylor rule fundamentals by Molodtsova and Papell (2009). However, in reaction to the global financial crisis, the major central banks set short-term interest rates to a zero lower bound (ZLB) which renders the conventional monetary policies ineffective. This has led to a debate among thought leaders on the efficacy of the Taylor rule.

The objective of this study is to check the effectiveness of the Taylor rule monetary policy in contemporary times by applying the Taylor rule fundamentals to forecast the exchange rates using current data and a new set of currency pairs. The research, therefore, contributes to the existing literature by investigating the usefulness of the Taylor rule-based exchange rate forecast in the pre- and post-crisis periods. More so, the study examines the sensitivity of the window size on the performance of the Taylor rule fundamentals. The research paper applies to four (4) OECD countries, namely, Norway, Chile, New Zealand and Mexico vis-à-vis the United States (U.S.). These countries adopt floating exchange rates with an inflation-targeting framework.

The impetus for selecting these countries includes the fact that Norway is one of the long-standing trading partners of the United States. Norway invests about 35% of its government pension fund in the U.S. Bloomberg (2019) reported that Norway plans to increase its wealth fund by USD 100 billion in U.S. stocks[1]. This shows that their economies and the exchange rate could be affected by the Taylor rule policy. However, the Norwegian exchange rate has received less research. Chile and Mexico were selected for this research because they are among the seven largest economies in Latin America that are emerging economies and have a floating exchange rate and inflation target framework. These countries contribute to the research by depicting how the Taylor rule monetary policy affects the exchange rates of the emerging economies in Latin America. New Zealand is the first country to implement the inflation-targeting framework in the early 1990s. Therefore, the Reserve Bank of New Zealand would exhibit a greater experience of the Taylor rule policy. These countries have chronological market relations regarding trading with the U.S. Their economies rely very much on the importation and exportation of goods and services.

Moreover, the Triennial Survey by the Bank for International Settlements (BIS) (2019) shows that the U.S. dollar is the most traded currency and the U.S. has been the center for international trading over the years. In 2019, the U.S. dollar contributed 88.3% of the total foreign exchange market volume. In 2019, the New Zealand dollar was ranked 11th among the global currencies trading, adding about 2.1% to the foreign exchange market volume. In the same currencies rankings, the Norwegian krone ranks 15th and the Mexican peso ranks 16th for contributing 1.8% and 1.7%, respectively. The U.S., Norway, Chile and New Zealand are noted as having "commodity currencies"[2] which influence the exchange rate changes (Chen et al. 2010). These features contribute to the choice of selecting the countries for this research.

The domestic country considered in this study is the U.S. An out-of-sample forecast is performed in the short horizon for the Norwegian krone, Chilean peso, New Zealand dollar and Mexican peso exchange rates with the U.S. dollar. The benchmark model is the random walk. A linear model is used in this work since it is shown to be the most efficacious exchange rate forecastability in the literature (Rossi 2013). The forecast would be evaluated by using the mean squared forecast error. For the forecast comparison, Molodtsova and Papell (2009) state that the linear model is nested; therefore, Clark and West's (2006, 2007) model is used to perform the significant test[3]. In this paper, similar models and specifications by Molodtsova and Papell (2009) are used.

It is important to stress that this study does not show which models beat the random walk but rather aims to show how accurately, significantly and reliably the Taylor rule fundamentals could forecast the exchange rate movements. Accuracy means that the forecasts are close to the values of the exchange rate. This follows a claim by Engel and West (2005) that the random walk performance is not a surprise but a result of rational expectations. This means that the exchange rate acts as a near-random walk and the random walk is not easy to beat (Diebold 2017).

The study seeks to shed light on these research questions: Can the Taylor rule fundamentals models accurately forecast currency exchange rates? How significant are the Taylor rule fundamentals in forecasting the exchange rate during the global financial crisis and great recession? Has the Taylor rule been effective in describing the exchange rate changes after the financial crisis? Can the exchange rate directions be forecasted by the Taylor rule fundamentals? In this paper, it is observed that the Taylor rule fundamentals could effectively describe and forecast the exchange rates until the financial crisis. In contrast, the Taylor rule fundamentals have been insignificant in forecasting exchange rates in the post-financial crisis. In addition, the choice of window size selection affects the forecast outcome of the models. The study shows that the smaller window size (60 observations) influences the Taylor rule fundamentals models to forecast the exchange rate better than the larger window size (120 observations).

The remainder of the study is structured as follows: Section 1.1 gives some literature reviews on the topic. Section 2 provides a theoretical framework, and details of the Taylor rule fundamentals are essential to this study. Section 3 describes the models and specifications for the forecast. Section 4 discusses the empirical framework, which also contains the data. Section 5 contains the main empirical test result, and Section 6 provides some economic analysis of the results. Section 7 concludes the study.

1.1. Literature Review

Recent research studies in the exchange rate forecast have advanced our knowledge of the exchange rate movement in the market. Some of the literature explains how Taylor rule fundamentals are used to forecast the exchange rate in different countries and with diversified approaches.

Molodtsova and Papell (2009) performed one month ahead of out-of-sample prediction of the exchange rate with the Taylor rule fundamentals for 12 OECD countries vis-à-vis the U.S. for the post-Bretton Woods period (from 1973 to 2006). Quasi-real-time data were used in their paper. Out of 16 specifications generated, they found a 5% level significant evidence of exchange rate forecast for 11 out of the 12 OECD Countries. Their strongest evidence results from the symmetric Taylor rule model with heterogeneous coefficients, interest rate smoothing and a constant. In addition, the paper finds strong evidence of exchange rate predictability with the Taylor rule fundamental models as compared to the conventional interest rates parity, purchasing power parity (PPP) and monetary models.

In addition, Molodtsova et al. (2011) used real-time quarterly data to find proof of out-of-sample predictability of the USD/EUR exchange rate based on the Taylor rule fundamentals. Another research by Molodtsova and Papell (2012) finds evidence of USD/EUR exchange rate predictability with the Taylor rule fundamentals during the financial crisis and the great recession.

Moreover, Ince (2014) applied real-time data to evaluate the out-of-sample forecast of the exchange rate with PPP and Taylor rule fundamentals using single-equation and panel methods. Using bootstrapped out-of-sample test statistics, Ince found that the Taylor rule fundamentals better forecast the exchange rate at the one-quarter-ahead. However, the Taylor rule fundamentals forecast performance is not improved with the panel estimation. Contrary to the Taylor rule fundamentals, the researcher found that the PPP model was better at forecasting the exchange rate in the longer horizon (16-quarter). Its forecast performance increases in the panel model relative to a single-equation estimation.

Byrne et al. (2016) contributed to the study by forecasting the exchange rates using the Taylor rule fundamentals and inculcating Bayesian models of time-varying parameters. They incorporated the financial crisis into their work and found that the Taylor rule fundamentals have the power to predict the exchange rate. Ince et al. (2016) extended the work by Molodtsova and Papell (2009) and demonstrated short-run out-of-sample predictability of the exchange rate with the two versions of the Taylor rule model for eight exchange rates vis-à-vis the U.S. dollar. Their research found strong evidence of exchange rate predictability with the Taylor rule fundamental model as compared to the Taylor rule differential and much stronger proof than the traditional exchange rate predictors. Cheung et al. (2019) performed exchange rate prediction redux and found the Taylor rule fundamentals outperform the random walk when the models' performances are measured with the mean squared prediction errors. However, they did not find statistically significant performance when the DMW test was conducted.

In addition to the basic linear model, Caporale et al. (2018) investigated the Taylor rule in five emerging economies through an augmented rule including exchange rates and a nonlinear threshold specification, which was estimated by the generalized method of moments. They found an overall performance of the augmented nonlinear Taylor rule to describe the actions of monetary authorities in these five countries.

Furthermore, Zhang and Hamori (2020) performed exchange rate prediction by combining modern machine learning methodologies (neural network models, random forest and support vector machine) with four fundamentals that include the Taylor rule models, uncovered interest rate, purchasing power parity and monetary model. Their root mean squared error and Diebold–Mariano test results prove that the fundamental models together with the machine learning perform better than the random walk.

2. Taylor Rule Fundamentals

Researchers have discovered that macroeconomics policies that center on the price level (inflation) and real output directly perform better than other policies such as money supply targeting. In 1993, John B. Taylor proposed that for a flexible exchange rate regime, the central bank adjusts its short-term interest rate target in response to changes in the price level (inflation rate) and real output (output gap) from a target as given in Equation (1):

$$\mathrm{i_t}^{\dagger} = \pi_t + \theta(\pi_t - {\pi_t}^{\dagger}) + \sigma \mathrm{y_t} + \mathrm{r}^{\dagger} \tag{1}$$

where $\mathrm{i_t}^{\dagger}$ is the target for the short-term nominal interest rate. π_t and ${\pi_t}^{\dagger}$ are the inflation rate and target level of inflation, respectively[4]. $\mathrm{y_t}$ is the output gap (percent deviation of actual real gross domestic product (GDP) from an estimate of its potential level) and $\mathrm{r}^{\dagger}$ is the equilibrium level of the real interest rate. The parameters θ and σ are the weights representing the central bank's reactions to the changes in the inflation rate and the output gap. Taylor assumes that inflation and output have the same weight of reaction (0.5 parameters each). Both the inflation target and the real interest rate are 2% at equilibrium. According to Taylor (1993), the short-term nominal interest rate would be raised by the Fed if the inflation rises over the target inflation level or the realized output is above the potential output and vice versa.

Molodtsova and Papell (2009) proposed fundamentals on the account of the Taylor rule monetary policy. The Taylor rule fundamentals suggest that when two economies fix their interest rates based on the Taylor rule, their interests would influence the exchange rate through the concept of uncovered interest rate parity. Now, following the asymmetric model by Clarida et al. (1998), the real exchange rate is added to the Taylor rule for the foreign countries. The idea is that the Fed sets the target level of the exchange rate to make PPP hold. That is, the nominal interest rate rises or falls if the exchange rate depreciates or appreciates from the PPP. This is expressed in Equation (2) below:

$$\mathrm{i_t}^{\dagger} = \pi_t + \theta(\pi_t - \pi_t{}^{\dagger}) + \sigma \mathrm{y_t} + \mathrm{r}^{\dagger} + \vartheta \mathrm{z_t} \tag{2}$$

where $\mathrm{z_t}$ is the real exchange rate and ϑ is the coefficient.

Also by the Clarida et al. (1998) smoothing model, Molodtsova and Papell (2009) assume in Equation (3) that the U.S. actual nominal interest rate adjusts to its target rate and lagged value. The lagged value is added since, in decision making, the central bank could not observe the ex-post-realized nominal interest rate. Hence, the lag value helps to account for delay adjustment.

$$\mathrm{i_t} = (1-\gamma)\ \mathrm{it}^{\dagger} + \gamma \mathrm{i_{t-1}} + \mathrm{v_t} \tag{3}$$

where γ is the coefficient of lag interest rate. Putting Equation (2) into (3) gives the interest rate reaction function of the U.S.

$$\mathrm{i_t} = (1-\gamma)\ [\pi_t\ + \theta\left(\pi_t - \pi_t{}^{\dagger}\right) + \sigma \mathrm{y_t} + \mathrm{r}^{\dagger} + \vartheta \mathrm{z_t}\Big] + \gamma \mathrm{i_{t-1}} + \mathrm{v_t} \tag{4}$$

where $\vartheta = 0$ for the U.S. if the real exchange rate approaches equilibrium. Molodtsova and Papell (2009) derive the Taylor rule fundamentals-based forecasting equation by subtracting the interest rate reaction function of the foreign country from the U.S. This results in an interest rate differential function represented in Equation (5).

$$\mathrm{i_t} - \mathrm{i_t}* = \alpha + \alpha_\pi \pi_t - \alpha_\pi \pi_t * + \alpha_\mathrm{y} \mathrm{y_t} - \alpha_\mathrm{y} \mathrm{y_t} * + \gamma \mathrm{i_{t-1}} - \gamma \mathrm{i_{t-1}} * - \alpha_\mathrm{z} \mathrm{z_t} * + \mathrm{v_t} \tag{5}$$

where * denotes foreign variables, the constants are: $\alpha_\pi = (1-\gamma)(1+\theta)$, $\alpha_\mathrm{y} = \sigma(1-\gamma)$, $\alpha_\mathrm{z} = \vartheta(1-\gamma)$, and $\alpha = (1-\gamma)(\theta\pi^* + \mathrm{r}^*)$, and $\mathrm{v_t}$ is the shock term.

The observation from Equation (5) is that, if the inflation rate rises over the target in the U.S. economy, the Fed responds to it by increasing the interest rate. It is worth noting that the monetary model of exchange rate implies an opposite relationship between interest rates and exchange rate, with higher domestic interest rate leading to an exchange rate depreciation. If uncovered interest rate parity (UIRP) holds, Dornbusch (1976) proposes that overshooting causes the U.S. dollar (USD) to later depreciate. It is empirically proven in most literature (Chinn and Quayyum 2012) that UIRP does not hold in the short run; hence, following Gourinchas and Tornell (2004), Molodtsova and Papell (2009) shows that the interest rate increment leads to a continuous rise in the USD.

According to the Taylor rule (1993), the appreciation of the USD causes the inflation rate in foreign countries to rise. Applying the symmetric model, the foreign central banks respond by increasing the foreign interest rate. Investors begin to move their capital from the U.S. to foreign countries, since there would be higher returns on foreign investment. The demand for the USD diminishes, the exchange rate immediately appreciates up to the point where the interest rate differential equals the expected depreciation, and the dollar starts to depreciate (forward premium).

Another reaction from the Taylor rule (1993) is that if the U.S. output gap increases, the Fed raises the Federal funds rate by α_y, causing the USD to appreciate. By contrast, if the foreign country's output gap increases and follows the Taylor rule, its central bank raises its interest rate, causing the USD depreciation. Moreover, the foreign central bank raises its interest rate when it observes a fall in its real exchange rate. This leads to a fall in the demand for the USD and immediate or forecasted depreciation. If the countries practice the smoothing model, a higher lagged interest rate increases current and expected future interest rates, which leads to an immediate and sustained USD appreciation. However, a higher lagged foreign interest rate causes a current or expected fall in the U.S. interest rate, and the USD is predicted to depreciate. From the rational expectations and the predictions explained above, it is observed that interest rate shocks that cause the central banks to respond to interest rate adjustment also have an impact on the exchange rate. Combining the analyses from Equation (5), the Taylor-rule-based exchange rate forecasting equation is developed as:

$$\Delta s_{t+1} = \beta - \beta_{\pi}\pi_t + \beta^*{}_{\pi}\pi_t{}^* - \beta^*{}_y y_t * - \beta i_{t-1} + \beta^* i_{t-1} * + \beta^*{}_z z_t * + v_t \tag{6}$$

where s_t is the log of the U.S. dollar nominal exchange rate taken as the domestic price of foreign currency and Δs_{t+1} is the change in the nominal exchange rate. β_i represent the parameters of the forecasting equation.

3. Model Description

Rossi (2013) explains how successful the linear equation model has been in forecasting the exchange rate. Therefore, a single-equation linear model as represented in Equation (6) is analyzed in this research. The same specifications proposed by Molodtsova and Papell (2009) would be used in this paper. Firstly, as proposed in Taylor (1993), there is a symmetric model ($\beta_z{}^*$ = 0) if the Fed and the foreign central banks follow the same rule to set the nominal interest rate based on current inflation, inflation gap (actual–target inflation), the output gap (actual–potential GDP) and equilibrium real interest rate. If the foreign central bank adds the real exchange rate to its Taylor rule ($\beta_z{}^* \neq 0$), it is described as an asymmetric model (Clarida et al. 1998).

Secondly, smoothing is considered, which is the interest rate expressed on its lag variable ($\beta_i \neq 0$, $\beta_i{}^* \neq 0$). Contrary, without interest rate lag it is termed as no smoothing ($\beta_i = 0$, $\beta_i{}^* = 0$). The third model used in Molodtsova and Papell (2009) is homogeneous. This occurs when the domestic and foreign central banks have the same parameter in their Taylor rule fundamental variables ($\beta_\pi = \beta_\pi{}^*$, $\beta_y = \beta_y{}^*$, $\beta_i = \beta_i{}^*$). However, if their response parameters are not the same, the heterogeneous model would be constructed for it ($\beta_\pi \neq \beta_\pi{}^*$, $\beta_y \neq \beta_y{}^*$, $\beta_i \neq \beta_i{}^*$). Constant ($\beta \neq 0$) and no constant ($\beta = 0$) are constructed as the fourth model. If the domestic and foreign central banks do not have the same target inflation rates and equilibrium real interest rates, a constant is added to the right-hand side of the equation and vice versa. The specifications by Molodtsova and Papell (2009) are modified to construct 16 models for this research as below:

Model 1: Symmetric, Smoothing, Homogeneous Coefficients and a Constant $\{\beta\ \pi_t - \pi_t{}^*\ y_t - y_t{}^*\ i_{t-1} - i_{t-1}{}^*\}$
Model 2: Symmetric, Smoothing, Homogeneous Coefficients and no Constant $\{\pi_t - \pi_t{}^*\ y_t - y_t{}^*\ i_{t-1} - i_{t-1}{}^*\}$
Model 3: Symmetric, Smoothing, Heterogeneous Coefficients and a Constant $\{\beta\ \pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\ i_{t-1}\ i_{t-1}{}^*\}$
Model 4: Symmetric, Smoothing, Heterogeneous Coefficients and no Constant $\{\pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\ i_{t-1}\ i_{t-1}{}^*\}$
Model 5: Symmetric, no Smoothing, Homogeneous Coefficients and a Constant $\{\beta\ \pi_t - \pi_t{}^*\ y_t - y_t{}^*\}$
Model 6: Symmetric, no Smoothing, Homogeneous Coefficients and no Constant $\{\pi_t - \pi_t{}^*\ y_t - y_t{}^*\}$
Model 7: Symmetric, no Smoothing, Heterogeneous Coefficients and a Constant $\{\beta\ \pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\}$
Model 8: Symmetric, no Smoothing, Heterogeneous Coefficients and no Constant $\{\pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\}$
Model 9: Asymmetric, Smoothing, Homogeneous Coefficients and a Constant $\{\beta\ \pi_t - \pi_t{}^*\ y_t - y_t{}^*\ i_{t-1} - i_{t-1}{}^*\ z_t{}^*\}$
Model 10: Asymmetric, Smoothing, Homogeneous Coefficients and no constant $\{\pi_t - \pi_t{}^*\ y_t - y_t{}^*\ i_{t-1} - i_{t-1}{}^*\ z_t{}^*\}$
Model 11: Asymmetric, Smoothing, Heterogeneous Coefficients and a constant $\{\beta\ \pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\ i_{t-1}\ i_{t-1}{}^*\ z_t{}^*\}$

Model 12: Asymmetric, Smoothing, Heterogeneous Coefficients and no Constant $\{\pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\ i_{t-1}\ i_{t-1}{}^*\ z_t{}^*\}$
Model 13: Asymmetric, no Smoothing, Homogeneous Coefficients and constant $\{\beta\ \pi_t - \pi_t{}^*\ y_t - y_t{}^*\ z_t{}^*\}$
Model 14: Asymmetric, no Smoothing, Homogeneous Coefficients and no Constant $\{\pi_t - \pi_t{}^*\ y_t - y_t{}^*\ z_t{}^*\}$
Model 15: Asymmetric, no Smoothing, Heterogeneous Coefficients and Constant $\{\beta\ \pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\ z_t{}^*\}$
Model 16: Asymmetric, no Smoothing, Heterogeneous Coefficients and no Constant $\{\pi_t\ \pi_t{}^*\ y_t\ y_t{}^*\ z_t{}^*\}$

4. Empirical Framework

4.1. Benchmark Model and Window Sensitivity Selection

The choice of benchmark and window size usually has an impact on the forecast results. After Meese and Rogoff (1983), it has been widely debated in most studies that the exchange rate follows a random walk. This implies that the exchange rate has a minimal chance of forecasting. There are two forms of random walk models discussed by Rossi (2013). These include a random walk without drift: $\Delta s_{t+1} = 0$. This is a martingale difference, which means that the current exchange rate steps from the previous exchange rate observation. Another form of a random walk considered in the literature is a random walk with drift. This is shown as $\Delta s_{t+1} = \delta_t$, where δ_t is a drift term included in the random walk. The drift can be thought of as determining a trend in the exchange rate. The exchange rate forecast surveyed by Rossi (2013) affirms that random walk without drift as a benchmark performs better than with drift. Therefore, in this paper, the random walk without drift is used as the benchmark.

Inoue and Rossi (2012) have shown that rolling windows of small size are more helpful to check predictive power. Although larger window size reduces the effect of outliers, Elliott and Timmermann (2016) explain that larger window size sometimes includes past data which are not important for current prediction. Hendry et al. (2019) add that a smaller window size excludes irrelevant information that might cause forecast failure. In this study, the empirical analysis is performed with a fixed-length rolling window with a 60 window size for the estimation.

4.2. Data Description

The countries under study include Norway, Chile, New Zealand and Mexico vis-à-vis the United States of America. The currencies include U.S. dollar (USD), Norwegian krone (NOK), Chilean peso (CLP), New Zealand dollar (NZD) and Mexican peso (MXN). Considering the indirect quotation of the exchange rate data, the USD is used as the base currency in this study. Monthly data of each country from 1995M1 to 2019M12 are applied to the estimation and forecasting of the exchange rate and includes a key financial phenomenon such as the 2008 global financial crisis which affected the foreign exchange movement. The raw data used include the foreign exchange rates (S_t), interest rate (i_t), income (output) (y_t) and prices (p_t)[5]. The consumer price index (CPI) is used to measure the price level in the economy. The federal funds rate is used as a short-term interest for the U.S. The money market rates are used as the short-run interest rate for Norway, New Zealand and Mexico. The deposit rates are used as the short-run interest rate for Chile since there were no available money market rate data. The industrial production (IP) index is used to replace countries' national income because GDP data are not consistently published.

From 1995, enormous fluctuations in the exchange rates have been experienced in the countries. The dot-com boom between 2000 and 2001 led to economic growth in the U.S. As a result, the NOK, CLP, NZD and MXN currencies depreciated against the USD. Norway introduced inflation targeting in 2001 after the NOK depreciated highly in 2000 and the USD/NOK exchange rate reached 9.65. During the 2007–2008 financial crisis, the USD depreciated, and the NOK, CLP, NZD and MXN appreciated. This caused their exchange rates against the USD to fall. For instance, in 2008, the USD/NOK declined to about 4.94. The exchange rates immediately increased in 2009 when the USD appreciated against the other currencies. However, commodity currencies such as NOK, CLP and NZD quickly appreciated due to a boom in commodities prices in 2009. The depreciation of the NOK, CLP, NZD and MXN against the USD was observed in 2019. The MXN has especially been on an incessant path of depreciation against the USD due to loss of productivity in Mexico comparative to the U.S. (see Figure 1 for details).

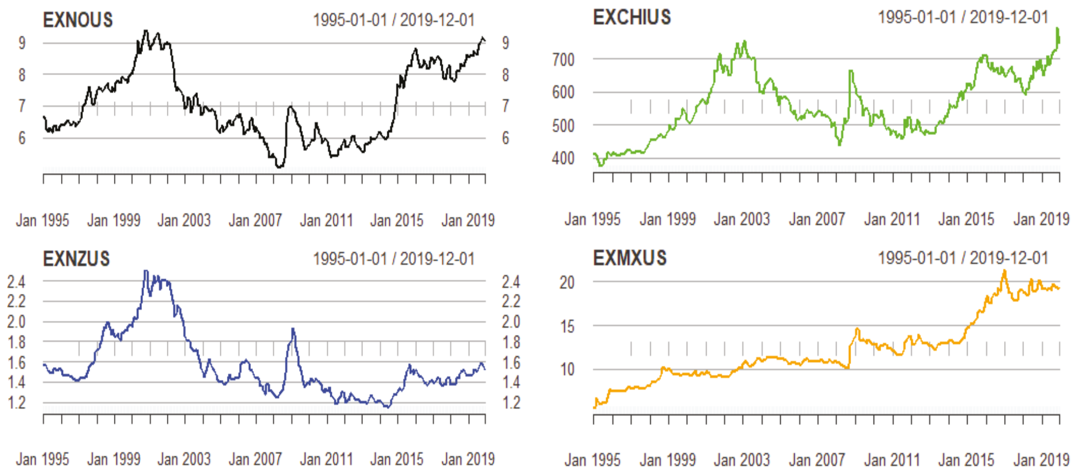

Figure 1. Foreign exchange rates.

The output gap (y_t) in this paper is measured as the percentage deviation of actual output from a Hodrick and Prescott (1997) (HP) generated trend[6]. This is because there is no standard description of potential GDP used in the central banks' interest rate reaction function. There are other alternatives measures of the output gap for example percentage deviations of actual output from a linear time trend or a quadratic time trend. However, the HP trend is proven to be a more accurate measure than the other two measures (Ince and Papell 2013). All variables except interest rates are in logarithms. The raw data are combined to construct data for the forecast models[7].

4.3. Estimation and Out-of-Sample Forecasting

From one to three months-ahead out-of-sample forecast for USD/NOK, USD/CLP, USD/NZD and USD/MXN exchange rates are generated. The reason for the multistep is to check how the models forecast the exchange rates as the forecast horizon increases. The 16 models in Section 3 are estimated by the ordinary least squared (OLS) using rolling windows (Molodtsova and Papell 2009). In the time-series data, periods 1995M1 to 1999M12 are used for the estimation and the remaining for the out-sample forecast. Thus, the first 60 observations of the time-series data are used to perform the first-month out-of-sample forecast in observation 61. The first data point is dropped, and observation 61 is added in the estimation sample and estimates the model over to forecast observation 62. The process is continued to extract the forecast error vector. A similar procedure is done for the 2 and 3 months-ahead out-of-sample forecast.

4.4. Forecast Assessment Approach

There are different loss functions used in evaluating the out-of-sample forecast. These include mean squared error (MSE), mean absolute error (MAE) and root mean squared error (RMSE) (Meese and Rogoff 1983). MAE is less affected by outliers. RMSE gives a positive root value and is easy to interpret. RMSE has a monotonic transformation and gives the same ordering as the MSE in even the asymptotic test. MSE has a measure of robustness. In this study, the MSE is best suitable for evaluating the forecast since the linear regression model is used. For simplicity, the MSE is referred to as mean squared forecast error (MSFE). This is calculated below:

$$\mathrm{MSFE} = \mathrm{P}^{-1} \sum\nolimits_{t=T-P+1}^{T} \left(\mathrm{y}_{\mathrm{t}+\tau} - \hat{y}_{\mathrm{t},\, \mathrm{t}+\tau}\right)^2 \tag{7}$$

where $\mathrm{y}_{\mathrm{t}+\tau}$ is the realized value at time t+τ, which in this paper is known as ($\Delta s_{\mathrm{t}+1}$). $\hat{y}_{\mathrm{t},\, \mathrm{t}+\tau}$ is the forecasted value. The difference gives us the error term. T + 1 and P equal the number of sample observations and the number of forecasts, respectively. According to Clark and West (2006), with a random walk, $\hat{y}_{\mathrm{t},\, \mathrm{t}+\tau} = 0$. The exchange rate forecastability is evaluated with the Taylor rule fundamental for Norway, Chile, New Zealand and Mexico by calculating the relative MSFEs (ratio of MSFE). That is, the MSFE of the random walk without drift is divided by the MSFE of the Taylor rule fundamentals model. If the result is greater than 1, then it implies that the Taylor rule fundamentals forecast model has a lower loss function than the random walk. Therefore, the Taylor rule fundamentals could perform better in exchange rate forecasts than the random walk.

4.5. Out-of-Sample Forecast Comparison Method

The significance test of the forecast accuracy of the linear model against the random walk model was proposed by Diebold and Mariano (1995) and West (1996). The DMW test tests for equal accuracy of the benchmark (random walk) and the alternative of linear forecastability (Taylor rule fundamentals) using the mean of their loss functions. This test is suitable for the non-nested models where the variables in one model are not contained in the other models. However, Molodtsova and Papell (2009) believe the forecast Equation (6) is nested and the DMW test could not appropriately be used. That is, if the DMW test is applied, the normal standard critical values would lead to few rejections of the random walk model since the MSFE of the random walk would be smaller than the alternative[8]. Therefore, Clark and West (2006, 2007) are applied to perform the significance test or the forecast accuracy (check Appendix A for details).

4.6. Directional Accuracy Test

Having tested the significance of the Taylor rule fundamental forecast model, it is important to investigate the directional accuracy of the model. Knowing the correct forecasts about signs of the exchange rate movement is profitable for investors and stock market traders. Moreover, it is of value for the central banks to comprehend the directional changes in the exchange rate to make prudent decisions. The directional accuracy of the forecast is tested in this study by applying the popular nonparametric test developed by Pesaran and Timmermann (1992). The statement of the hypothesis of the Pesaran and Timmerman (PT) test is given as the actual and the forecasted exchange rate values bearing no relationship among them. This implies that the actual and forecasted values are independently distributed; hence, the directional signs could not easily be predicted. The PT test statistics converge to a standard normal distribution. The test statistics have critical values of 1.64 (0.05 test) and 2.33 (0.01 test). Conferring to Brooks (1997) and Clark and West (2006), the forecast of the random walk is always zero; hence, only the directional sign of the Taylor rule fundamentals model is tested.

5. Empirical Test Results

5.1. Stationarity Test (Unit Root Test)

In forecasting, it is relevant to test for stationarity. The exchange rate and the macroeconomics variable or the economic fundamentals in Equation (6) can follow nonstationarity, which may lead to spurious regression. Hence, before the OLS estimation is computed, the Dickey and Fuller (1979) model was used to test for the unit root. The augmented Dickey–Fuller (ADF) test soaks up the autocorrelation so that the error term becomes independently identically distributed white noise. The null hypothesis is a unit root. The decision test is to reject the null hypothesis if the test statistic (z(t)) is less than the critical values. This implies that the regression is stationary and suitable for the model forecast.

In this paper, the unit root test is examined with three models. Model 1 is a time series without both constant and trend. Model 2 tests the unit root in a time series with constant and without trend, because some variables such as exchange rates are expected to be in equilibrium in the long run. In addition, some fundamentals such as the price level and the industrial production level in the forecast equation change with time. Therefore, the ADF tests are modeled with a constant and a time trend (model 3). In total, 35 cases are tested using 90% confidence intervals across the five countries. In 28 out of the 35 cases, the null hypothesis of the unit root is rejected, and in seven cases, the null hypothesis fails to be rejected. The results show that change in the exchange rate (Δs_{t+1}) is stationary in Norway, Chile, New Zealand and Mexico at a 1% significance level. The lag interest rate (i_{t-1}) under model 2 is stationary for Chile and Mexico at 5% and 1% significance level, respectively, while it is nonstationary for Norway, New Zealand and the U.S. The inflation rate (π_t) is stationary for all the countries with a trend, although the trend is not significant for most of the countries in which the constant happens to be significant.

Moreover, the output gap (y_t) is stationary for all the countries at a 1% significant level except for the United States, which is nonstationary. With the real exchange rate (z_t), the unit root fails to be rejected for all the countries. The homogeneous models, which are the lag interest rate difference, inflation rate difference and the output gap difference, are shown to be stationary for all the countries. The unit root with lag interest rate difference for New Zealand is rejected with a drift term. In summary, Norway and New Zealand have fundamental variables that have all been stationary except lag interest rate and real exchange rate. Chile and Mexico have fundamental variables that have all been stationary except real exchange, and the U.S. has only the inflation rate as stationary. The nonstationary variables are tested with their first difference, and they turned out to be stationary. However, applying the first difference creates challenges with the interpretation of the result[9] (check Table A1 in Appendix B for details). There is enough evidence that the fundamental variables are stationary, and therefore the OLS estimation and forecasting could be performed.

5.2. Taylor Rule Fundamentals Model

The empirical results of the Taylor rule fundamentals models are summarized in Table 1 below, which contains accurate or significant models.

Table 1. Summary of the accurate Taylor rule fundamentals (60 window size).

	Norway	Chile	New Zealand	Mexico
	Accurate Models	**Accurate Models**	**Accurate Models**	**Accurate Models**
Full Sample—One Month Ahead	3, 4, 7, 11, 12, 15, 16	None	1, 3, 4, 6, 7, 8, 9, 10, 11, 12, 16	1, 7, 16
Until the Financial Crisis	2, 3, 6, 7, 12, 15, 16	None	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 14, 15, 16	1, 2, 3, 6, 7, 10, 12, 16
Post-Financial Crisis	None	None	1, 3, 11	1, 10
Full Sample—Two Months Ahead	7, 12, 16	None	1, 3	None
Full Sample—Three Months Ahead	7, 16	None	3	None

Table 1 reports the Taylor rule fundamentals models that could accurately forecast the exchange rates. The Clark and West statistics are used for the significant test using a window size of 60 under rolling regression.

5.2.1. One Month-Ahead Forecast

A one month out-of-sample forecast is performed with the full sample data. A window size of 60 is used for the OLS estimation from 1995M1 to 1999M12. The remaining data are used for the forecasts[10]. In evaluating the forecast, the relative mean squared forecast error (R.MSFE) is constructed for the random walk without drift model and the Taylor rule fundamentals model. The results in Table A2 in Appendix C show that the R.MSFEs are less than one for the four countries. This means the random walk outperforms the Taylor rule fundamentals when their performances are evaluated with the loss function. This indicates that the exchange rate may be closer to a random walk, and forecast practitioners would not find it easy to beat the random walk (Diebold 2017; Hendry et al. 2019; Engel and West 2005). It is, therefore, imperative to judge forecast based on the model accuracy using the Clark and West (2006, 2007) statistics as discussed in Appendix A.

From Table 1 above, evidence of 11 models is found to accurately forecast the New Zealand exchange rate, seven models for Norway and two models for Mexico. There is no evidence of forecastability for Chile[11]. Table A2 in Appendix C gives the details of the forecast accuracy for the one month out-of-sample for the 16 models using CW statistics under a rolling window. Strong results are found for the exchange rate forecastability with the models using heterogeneous coefficients. Among the Taylor rule fundamentals, the study finds the strongest evidence of forecastability for symmetric with no interest rate smoothing, heterogeneous coefficients and with a constant (model 7). Model 7 constitutes the inflation rate and output gap as described in the original Taylor rule. Model 7 accurately or significantly outperforms the random walk (null hypothesis) in three out of four countries (Norway at a 1% significance level, New Zealand at a 5% significance level and Mexico at a 10% significance level).

When the real exchange rate is added, a strong performance is observed with its asymmetric model 16, which includes inflation rate, output gap and the real exchange rate. This model is significant for three out of four countries (Norway at a 1% significance level, New Zealand at a 5% significance level and Mexico at a 10% significance level). From Tables 1 and A2, model 3 (symmetric with interest rate smoothing, heterogeneous coefficients with a constant) and model 12 (asymmetric with interest rate smoothing, heterogeneous coefficients without a constant) also significantly outperform the random walk model. These two models find evidence of the exchange rate forecast in two out of the four countries (Norway, New Zealand at a 1% significance level, respectively).

5.2.2. Until the Financial Crisis

This section answers the following research question: how significant are the Taylor rule fundamentals in forecasting the exchange rate during the global financial crisis and the great recession? The study ensured the findings are not only driven by the selection of the whole sample period. Therefore, the usefulness of the Taylor rule fundamentals for the pre- and post-crisis periods forecasting exchange rates is demonstrated.

To examine the effect of the financial crisis, the sample is adjusted to cover from 1995M1 to 2008M12 and performed the out-of-sample forecast using 60 window size.[12] From Table 1, the persistence of the Taylor rule fundamentals forecast accuracy is observed for Norway, New Zealand and Mexico. Again, the Taylor rule models are not significant for Chile. During the period of the 2008 financial crisis, the number of significant models of the Taylor rule fundamentals increased to 14 models for New Zealand. The significant models increased to eight for Mexico, while it remained at seven models for Norway. This means that irrespective of the financial instability in 2008, the Taylor rule fundamentals model was more prescriptive of or more accurately forecasted the exchange rates than the random walk model[13]. Again, models 7 and 16 strongly outperform the random walk in Norway, New Zealand and Mexico. Even for the forecast evaluation by the relative MSFE, where it is hard to beat the random walk, results in Table A3 in Appendix C show that New Zealand with models (1, 5, 6, 7, and 14), Mexico with models (1, 2, 6, 7, 9, 10, 15, and

16) and Norway with models (2 and 6) perform better than the random walk during the financial crisis.

5.2.3. Post-Financial Crisis

The impact of the Taylor rule fundamentals model on the exchange rate forecasts in the post-financial crisis period is considered. The data sample ranges from 2009M1 to 2019, except for New Zealand which starts from 2009M1 to 2017 due to the unavailability of data[14]. Though the sample might not be enough for the forecast analysis, the summary result in Table 1 shows that the models have not been significant. There is no significant model for Norway and Chile, and only three models and two models show evidence of forecastability for New Zealand and Mexico, respectively. Details of the CW test statistics are presented in Table A4 in Appendix C. With the forecast evaluation, New Zealand has model 3 outperforming the random walk. While Chile has models 2 and 6 evaluated to perform better than the random walk, they turn out to be insignificant with the CW test. It could be observed that the performance of Taylor rule fundamentals in forecasting the exchange rates has not been effective after the financial crisis.

5.2.4. Two–Three Month's Out-of-Sample Forecast

To this extent, a one month out-of-sample forecast was used to demonstrate the performance of the Taylor rule fundamentals models. It would be interesting to check how the Taylor rule could be applied to forecast the respective exchange rates in the multi-step ahead. The motivation for this section is to compare the effectiveness of the Taylor rule in forecasting the exchange rates as the forecast horizon increases. Because the paper investigates the short horizon, the analysis is extended to a 2 and 3 months-ahead out-of-sample forecast. However, as discussed in Appendix A, multistep-ahead forecast errors follow a moving average or a serial correlation (Clark and West 2007)[15]. For a robust regression, the Newey–West estimator with lag 4 is applied to compute the CW inference.

The CW statistics results of the 2 and 3 months-ahead forecasts represented in Table 1 show that none of the 16 models could significantly forecast the exchange rate in Chile and Mexico. Norway has only three significant models (models 7, 12, and 16) for the 2 months-ahead forecasts, and two models (models 7, 16) were significant at a 10% level for the 3 months-ahead forecasts. In addition, New Zealand has just 2 out of the 16 models (models 1 and 3) that were significantly accurate at a 5% level for the 2 months, and only model 3 was accurate at a 5% significant level for 3 months-ahead forecasts (check Tables A5 and A6 in Appendix C). By and large, the results show that the Taylor rule fundamentals do not accurately forecast the exchange rates in the 2 and 3 months ahead[16].

5.3. Directional Accuracy

The directional accuracy is tested using Pesaran and Timmermann (1992). This gives the percentage changes of the exchange rates that were accurately forecasted by the Taylor rule fundamentals models. The PT test is performed on only the one month-ahead forecast because the multistep-ahead forecasts are not significant. Using the full sample data, the PT test results in Table A7 (Appendix C) show that the models could not successfully forecast the directional change for both Norway and Chile exchange rates (only model 14 tests were significant for Norway at 10% level). However, 10 out of the 16 models (models 1, 3, 6, 7, 8, 10, 11, 12, 15, and 16) have strong evidence of forecasting the directional change for the New Zealand exchange rate. New Zealand has at least 50.47% of the directional sign of the exchange rate change accurately forecasted. In addition, for Mexico, four models (models 1, 3, 10, and 12) successfully forecast the directional change. The best performing models are the heterogeneous coefficients models.

To get a clear picture of the directional change of the exchange rates with our Taylor rule fundamentals model, the sample adjustment is considered. The data sample until the financial crisis is used just as it is done for the forecast accuracy. It is observed from the PT test results in Table A8 that the models' performance in checking the directional change of the exchange rate improved until the financial crisis. At this period, the significance performance of the models for the USD/NZD exchange rate increased to 13 models (except models 4, 11, and 13). The minimum directional accuracy of the New Zealand exchange rate is 55.56%. There are five significant models (models 1, 2, 3, 10, and 12) for the USD/MXN exchange rate and three successful models (models 7, 14, and 16) for the USD/NOK exchange rates. However, the Taylor rule models are again not effective in forecasting the direction of the USD/CLP exchange rate.

From Table A9, the models have not been successful in forecasting the direction of the four exchange rate changes in the post-financial crisis period. The significant models for New Zealand decreased to four models. This shows that the Taylor rule models could not effectively predict the directional change of the exchange rates in the post-financial crisis period. By and large, considering the PT test results, the analysis concludes that the directional accuracy or sign change of the USD/NZD exchange rate could be forecasted by the Taylor rule fundamentals models. The results for the directional accuracy in the case of the USD/MXN exchange rate to some degree are inconclusive.

5.4. Window Sensitivity

Corresponding to Section 4.1, the rolling window size is changed from 60 to 120. That is, the period from 1995M1 to 2004M12 is used for the estimation and the remaining data for the out-of-sample forecast. This helps to investigate the impact of larger window size on the Taylor rule models out-of-sample forecast of the exchange rate. The CW statistics results are summarized in Table 2 below.

Table 2. Summary of the accurate Taylor rule fundamental (120 window size).

	Norway	Chile	New Zealand	Mexico
	Accurate Models	**Accurate Models**	**Accurate Models**	**Accurate Models**
Full Sample—One Month Ahead	3, 4, 7, 11, 12, 15, 16	None	3, 7	None
Until the Financial Crisis	3, 7, 12, 15, 16	None	None	3, 4, 5, 6, 8, 12, 14
Post-Financial Crisis	None	2, 5, 6, 7, 8, 11 14, 16	None	1, 10
Full Sample—Two Months Ahead	7, 16	None	None	None
Full Sample—Three Months Ahead	None	None	None	None

Table 2 reports the Taylor rule fundamentals models that could accurately forecast the exchange rates. The Clark and West statistics are used for the significant test using a window size of 120 under rolling regression.

From Table 2, an overall reduction in the performance of the Taylor rule fundamentals in forecasting the exchange rates could be observed. When the one month-ahead forecast is performed for the full sample, there is no significant model found for Chile and Mexico. New Zealand has two significant models, and Norway has seven significant models. The best-performing models are heterogeneous coefficients and constants. The strongest evidence of the Taylor rule fundamentals models is model 7 (symmetric with no interest rate smoothing, heterogeneous coefficients and with a constant). This was the same model that performed best when the 60 window size was used for the estimation (check Table A10 in Appendix D for details).

The sample adjustment was examined with the 120 window size. The sample until the financial crisis is used and has no significant evidence of forecastability for Chile and New Zealand. This is interesting because 14 significant models were found for New Zealand with 60 window sizes. The significant models were reduced to five models for Norway and remained at seven models for Mexico (check Table A11 in Appendix D for detail).

The post-financial crisis period was examined from 2009M1 to 2019M11. None of the models could significantly outperform the random walk for USD/NOK and USD/NZD exchange rates[17]. Mexico had two significant models. Chile had eight models significantly outperforming the random walk[18] (see Table A12 for details).

The Taylor rule fundamentals out-of-sample forecast for the 2 and 3 months-ahead forecast with the 120 window size was performed. The results in Tables A13 and A14 in Appendix D show that the models do not significantly outperform the random walk model. Only models 7 and 16 are accurate for the 2 months-ahead forecast for Norway. In addition, the PT test is performed and found no directional accuracy of the USD/CLP and USD/MXN exchange rates. However, four heterogeneous coefficient models show evidence of directional accuracy for the USD/NOK exchange rate at a 10% significant level. Four models significantly evaluate the directional sign of the USD/NZD exchange rate (check Table A15 for details). It gets tougher for the Taylor rule fundamentals model to forecast the directional change of the exchange rate when the larger window size is used. These analyses prove that the choice of window size selection affects the forecast outcome of the models. It is observed that the smaller window size (60 observations) influences the Taylor rule fundamentals models to forecast the exchange rate better than with the larger window size (120 observations).

6. Economic Analysis and Discussions

Taylor (1993) presents monetary policy rules that describe the interest rate decisions of the Federal Reserve's Federal Open Market Committee (FOMC). The Taylor rule specifies the short-run interest rate response to changes in the inflation rate and the output gap. Molodtsova and Papell (2009) derived the Taylor rule fundamentals by subtracting the Taylor rule of the foreign countries from the Taylor rule of the domestic country (U.S.) with some model specifications. They had their strongest evidence coming from the specifications that included heterogeneous coefficients and interest rate smoothing.

In this paper, similar specifications were used with 16 different models to examine how the Taylor rule fundamentals could be applied to forecast the exchange rates. The study used four OECD countries (Norway, Chile, New Zealand and Mexico) vis-à-vis the U.S. When the out-of-sample forecast for the full sample with the loss function was evaluated, the Taylor rule fundamentals models could not outperform the random walk without drift. This is a stylized fact in a forecast in which the random walk is hard to beat (Diebold 2017; Hendry et al. 2019). It implies that the noise surrounding the Taylor models is little, but if the wrong model is selected for the out-of-sample forecast, it would produce a big error that would overcompensate the decreased size of the noise. Then, the random walk would perform better than the linear model. Therefore, the significance of the Taylor rule fundamentals models is investigated by testing their forecast accuracy with the Clark and West (2006, 2007) statistics.

The strongest evidence comes from the models with heterogeneous coefficients, which is consistent with the result of Molodtsova and Papell (2009). The most performing model based on the empirical result analysis is model 7, which incorporates symmetric with no interest rate smoothing and heterogeneous coefficients with a constant. This implies that the inflation rate and output gap influence the changes in the exchange rates. The heterogeneous coefficient means that the Fed and the foreign central banks respond differently to change in the inflation rate and the output gap. The constant shows that the central banks do not have the same target inflation rates and equilibrium real interest rates. In addition, the symmetric model explains that the Fed and the foreign central banks follow the same Taylor rule model. When the real exchange rate is added to the models (asymmetric), the performance was again boosted. This shows that the central banks react to the adjustment of PPP, which influences the exchange rate movements.

The financial crisis causes a structural break in the sample data. Therefore, the coefficients might not be constant over time, and the model could favor the short-run period. Nikolsko-Rzhevskyy et al. (2014) test for multiple structural changes to examine the economic performance of the Taylor rule. In this study, the sample data are adjusted to cover the financial crisis and the great recession and realized evidence of exchange rate forecastability with the Taylor rule fundamentals models[19]. The interest rate data show that until the 2008 financial crisis, the central banks adjusted their interest rates to control inflation. Hence, the monetary policy became very active as the central banks followed the Taylor rule descriptions.

However, in the post-financial crisis period, the Taylor rule fundamentals could not forecast the exchange rate better than the random walk. The Fed lowered the interest rate to zero lower bound. Norway's interest rate also decreased close to the lower bound. In 2019, New Zealand lowered the interest rate to 1%. Mexico experienced a 3% interest rate from 2013 to 2015, and it increased to 4.5% in 2019. Chile's interest rate declined to 0.5% in 2009, increased after 2010 to 5% and then decreased after 2012 to 1.75% (check Figure 2). From the empirical analysis, the Taylor rule lost its efficacy in forecasting the exchange rates after the financial crisis because the interest rates hit the zero lower bound.

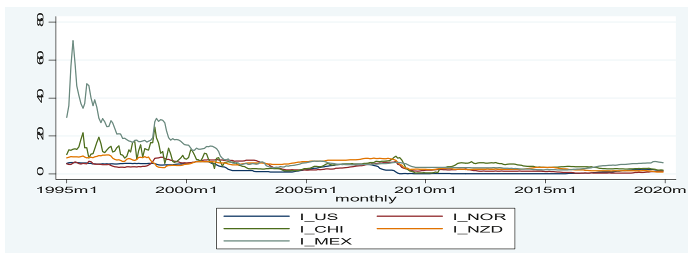

Figure 2. Nominal interest rates.

Taylor (2015) explained during the 2015 IMF conference that the Fed has not adhered to the prescription of the Taylor rule. This rendered the monetary policy as being passive. Most central banks set short-term interest rates to a zero lower bound (ZLB) in response to the financial crisis and have adopted quantitative easing or large-scale asset purchases (balance sheets) to pursue their policies. For the Taylor rule fundamentals to be more descriptive, the study suggests that the central banks control the interest rate lower bound. Following Ben S. Bernanke's (2015) presentation at the 2015 IMF conference, the Fed could also devise a monetary policy that would increase the inflation target, targeting the price level and targeting the output gap. If these variables are controlled by the central banks, the models would forecast the exchange rate better in the post-financial crisis period. In addition, Bernanke (2015) suggests mix monetary and proactive fiscal policies as they would ideally control the zero lower bound interest rate.

The empirical results in this paper also depict that policymakers could not accurately apply the Taylor rule fundamentals to forecast the USD/NOK, USD/CLP, USD/NZD and USD/MXN in the 2 and 3 months ahead. The model is significant in only the one month-ahead out-of-sample forecast.

Furthermore, central banks and asset managers or investors are usually interested in knowing the directional signs of the exchange rate in the market, as it equips them to efficiently and strategically decide either to sell or buy a security. The exchange rate directional accuracy was tested by applying the Pesaran and Timmermann (1992) test. The results show that the Taylor rule fundamentals models could accurately forecast the directional change of the USD/NZD exchange rate. This means that, other things equal, investing in New Zealand is more profitable compared to the other three countries since investors could forecast the exchange rate changes. The success of the directional accuracy of the New Zealand exchange rate change has a minimum of 50.47%. Except after the financial crisis where the Taylor rule has not been effective, Mexico's exchange rate has a potential for directional accuracy considering the PT test results. However, the PT test results for Norway and Chile depict difficulties in evaluating the directional exchange rate changes in these two economies.

7. Conclusions

In this research, the out-of-sample forecast is used to examine the application of the Taylor rule fundamentals in forecasting the exchange rates. To this end, an inference can be made that for the whole sample data, the Taylor rule fundamentals significantly forecast the exchange rates at the 1 month ahead using the Clark and West (2006, 2007) test. However, at the 2 and 3 months-ahead forecast horizon, weak evidence of exchange rates forecastability is realized with the Taylor rule fundamentals models against the random walk in the four countries. The best-performing model is symmetric with no interest rate smoothing and heterogeneous coefficients with a constant.

Taylor rule fundamentals models perform better in forecasting the exchange rates until the financial crisis. The Taylor rules' performance is observed to be insignificant in the post-financial crisis. This could be attributed to interest rates approaching the zero lower bound. Moreover, the study showed that the models' performance is sensitive to changes in the window size. The models perform better with small window size than with larger window size. New Zealand was the best-performing country and Chile the worst. It means that Chile slightly follows the Taylor rule for its monetary policy (Moura and Carvalho 2010; Moura 2010). For directional accuracy, the PT test demonstrates results in favor of the USD/NZD and USD/MXN exchange rates.

By and large, this study provides evidence of exchange rate forecastability with the Taylor rule fundamentals using the CW test statistics. However, the Taylor rule fundamentals do not put the estimated coefficients on the Taylor rule variables. Rather, the models only examine out-of-sample forecastability (Ince et al. 2016). Therefore, further investigation into the connection between the Fed using the Taylor rule and the out-of-sample exchange rate forecastability is needed. Given the experience that the Taylor rule has not been effective since after the 2008 financial crisis, there is also a need for a broader approach such as the use of a balance sheet of the central banks.

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Data Availability Statement: The data presented in this study are available publicly. All sources are cited in the study.

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Appendix A. Clark and West (CW) Test

The Clark and West (2006, 2007) test uses simulations to show the existence of linear forecastability in a given series, contrary to the null hypothesis that the series follows a martingale sequence or difference (also known as a random walk). They compare the out-of-sample MSFE of the random walk and the alternative of linear forecastability.

Model 1 is the parsimonious model (null model of random walk).

Model 2 is the nested large model (alternative model).

Given a linear regression as

$$y_t = \beta X_t^{'} + e_t \tag{A1}$$

where y_t is a dependent variable whose interest we want to predict (expected nominal exchange rate); $X_t^{'}$ is a vector of variables; and e_t is the error term. Clark and West state under the null hypothesis that $\beta = 0$ and under the alternative hypothesis that $\beta \neq 0$. They assume that under both hypotheses a martingale difference exists. This gives the conditional expectations of the errors being zero: $E_{t-1}e_t \equiv E(e_t \mid X_t, e_{t-1}, X_{t-1}, e_{t-2}, \ldots) = 0$

Let $\hat{y}_{1t,t+\tau}$ denotes the forecasts of model 1 at period *t* of $y_{t+\tau}$.

Where $\hat{y}_{2t,t+\tau}$ denotes the forecasts of model 2 at period t of $y_{t+\tau}$. τ is the forecast horizon, and $y_{t+\tau}$ is our actual value which is used as Δs_{t+1} in our analysis.

Model 1 errors equal $(y_{t+\tau} - \hat{y}_{1t,t+\tau})$, and model 2 errors equal $(y_{t+\tau} - \hat{y}_{2t,t+\tau})$

$$\mathrm{MSPE}_1 = \mathrm{P}^{-1} \sum_{t=T-P+1}^{T} (y_{t+\tau} - \hat{y}_{1t,t+\tau})^2 \tag{A2}$$

$$\mathrm{MSPE}_2 = \mathrm{P}^{-1} \sum_{t=T-P+1}^{T} (y_{t+\tau} - \hat{y}_{2t,t+\tau})^2 \tag{A3}$$

Clark and West (2006, 2007) solve the nested problem associated with the DMW test by introducing an adjustment term (adj).

$$\mathrm{adj} = \mathrm{P}^{-1} \sum_{t=T-P+1}^{T} (\hat{y}_{1t,t+\tau} - \hat{y}_{2t,t+\tau})^2 \tag{A4}$$

This gives the differences between the MSFE of the alternative hypothesis and the new adjustment term as $(\mathrm{MSFE}_2 - \mathrm{adj})$. Hence, Clark and West test the null hypothesis of equal MSFE.

$$\mathrm{H}_0 : \ \mathrm{MSFE}_1 = (\mathrm{MSFE}_2 - \mathrm{adj}) \tag{A5}$$

$$\mathrm{H}_1 : \ \mathrm{MSFE}_1 > (\mathrm{MSFE}_2 - \mathrm{adj}) \tag{A6}$$

After some computations:

$$\hat{f}_{t+\tau} = (y_{t+\tau} - \hat{y}_{1t,t+\tau})^2 - \left[(y_{t+\tau} - \hat{y}_{2t,t+\tau})^2 - (\hat{y}_{1t,t+\tau} - \hat{y}_{2t,t+\tau})^2\right] \tag{A7}$$

The mean then becomes:

$$\overline{f} = \mathrm{P}^{-1} \sum_{t=T-P+1}^{T} \left(\hat{f}_{t+\tau}\right) \tag{A8}$$

Clark and West (2006) states that if the test is against a random walk, the forecast of model 1 is just a constant value of zero, such that $\hat{y}_{1t,t+\tau}$ equals zero. Therefore, the MSFE_1 becomes the sample mean squared of the actual value (Δs_{t+1}). Thus, $\mathrm{MSFE}_1 = \mathrm{P}^{-1} \sum_{t=T-P+1}^{T} (y_{t+\tau})^2$. After some computation,

$$\hat{f}_{t+1} = 2(y_{t+1})(\hat{y}_{2t+1}) \tag{A9}$$

We then arrive at the test statistics:

$$\sqrt{P}\,\overline{f} / [\text{sample variance of} \hat{f}_{t+1} - \overline{f}]^{1/2}$$

For the one month-ahead forecast, the normal OLS standard error could be applied, since the forecast errors are white noise. However, Clark and West (2006, 2007) state that as the forecast horizon increases, there would be overlapping in the data in forecasting τ—steps ahead. Therefore,

$$\mathrm{MSPE}_1 = (\mathrm{P} - \tau + 1)^{-1} \sum_{t=T-P+1}^{T-\tau+1} (y_{t+\tau,\,\tau})^2 \tag{A10}$$

$$\mathrm{MSPE}_2 = (\mathrm{P} - \tau + 1)^{-1} \sum_{t=T-P+1}^{T} (y_{t+\tau,\,\tau} - \hat{y}_{2t,t+\tau})^2 \tag{A11}$$

According to Clark and West, the time series follows a moving average $(\tau - 1)$. That means there would be a serial correlation in the residuals. To solve this problem, Clark and West propose regressing a Newey–West robust variance estimator (Newey and West 1987) on $\hat{f}$. This results in $\hat{g}_t = 2y_t(\hat{y}_{2t,\,t+\tau})$. The sample mean becomes $\overline{g}$.

Consistent sample variance,

$$\hat{V} = (\mathrm{P} - 2\tau + 2)^{-1} \sum_{t=T-P+\tau}^{T-\tau+1} (\hat{g}_t - \overline{g})^2 \tag{A12}$$

Decision rule:

Clark and West's statistics follow a one-sided test that captures only the upper tail. This implies that if the test statistic is greater than +1.282 (0.10 test) or +1.645 (0.05 test), we reject the null hypothesis of a random walk model.

Appendix B. Stationarity Test (Augmented Dickey–Fuller Test)

Table A1. Unit root test with ADF.

	Norway		Chile		New Zealand		Mexico		U.S	
	M	T-Stat	M	T-Stat	M	T-Stat	M	T-Stat	M	T-Stat
Δs_{t+1}	2	−11.046 ***	2	−11.944 ***	2	−10.044 ***	2	−13.660 ***	-	-
i_{t-1}	2	−1.394	2	−3.188 **	2	−1.536	2	−3.533 ***	2	−1.616
π_t	3	−5.497 ***	3	−3.348 *	3	−3.240 *	3	−3.503 **	3	−5.073 ***
y_t	3	−5.635 ***	3	−12.589 ***	3	−10.567 ***	3	−4.561 ***	3	−2.957
z_t	2	−1.713	2	−1.830	2	−1.546	2	−2.568	-	-
$i_{t-1} - i_{t-1}{}^*$	1	−1.972 *	2	−4.402 ***	Drift	−2.007 **	2	−3.910 ***	-	-
$\pi_t - \pi_t{}^*$	3	−4.306 ***	2	−3.347 **	3	−3.567 **	1	−2.534 **	-	-
$y_t - y_t{}^*$	3	−6.109 ***	3	−13.307 ***	3	−10.118 ***	3	−5.091 ***	-	-
z_t(D)	2	−11.240 ***	2	−12.579 ***	2	−10.727 ***	2	−11.807 ***	-	-
i_{t-1}(D)	2	−8.737 ***	2	−14.847 ***	2	−8.104 ***	2	−13.135 ***	2	−5.980 ***

This table displays the stationarity results for the variables found in Equation (6). The augmented Dickey–Fuller is used to test the null hypothesis of a unit root (left-sided hypothesis). The decision test is that if the test statistic (z_t) is less than the critical value at either 1%, 5% and 10% significant level, and the null hypothesis is rejected. ***, ** and * mean the variable is stationary at 1%, 5% and 10% significant levels, respectively. The columns with M represent the model used for the stationarity test. Testing with model 1 shows that no constant, and no trend is added to the regression equation. Constant but no trend in the regression is explained by model 2. This implies that the fundamental variables are expected to move to equilibrium in the long run. Model 3 shows that we run the ADF test with both constant and trend since some of the variables such as prices and industrial production can change over time. z_t(D) and i_{t-1}(D) represent the first difference of the real exchange rate and the lag interest rate, respectively.

Appendix C. Out-of-Sample Forecast with 60 Window Size

Table A2. One month-ahead forecasts using Taylor rule fundamentals with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat
1	0.8982	0.8192	0.8529	−0.3793	0.9868	3.1196 ***	0.9324	1.3117 *
2	0.9244	0.9753	0.8904	−0.6690	0.9163	0.7625	0.9221	0.0089
3	0.8834	2.5139 ***	0.7563	0.5004	0.8964	3.5655 ***	0.7891	0.9487
4	0.8329	1.3197 *	0.7602	−0.3995	0.8504	1.4779 *	0.7849	−1.0651
5	0.9247	0.6476	0.9434	−0.4662	0.9507	0.8869	0.9273	0.0639
6	0.9649	0.9933	0.9617	−0.5418	0.9779	1.3359 *	0.9491	−0.3468
7	0.9637	3.2694 ***	0.8496	0.0465	0.9321	2.1055 **	0.9134	1.3351 *
8	0.8715	0.6963	0.8526	−0.9668	0.9105	1.4001 *	0.8935	−0.9495
9	0.8257	−0.8020	0.8435	−0.3542	0.9288	2.1614 **	0.9085	0.9310
10	0.8993	0.8944	0.8546	−0.3696	0.9207	2.2608 **	0.9298	1.2328
11	0.8444	1.6622 **	0.7340	−0.3737	0.8345	2.6262 ***	0.7408	0.4761
12	0.8981	2.6203 ***	0.7598	0.5393	0.8375	2.3610 ***	0.7781	1.0582
13	0.8781	−0.2905	0.8826	−1.2108	0.8767	−0.9117	0.9167	0.0532
14	0.9255	0.6613	0.9429	−0.4715	0.9517	0.9092	0.9265	0.0717
15	0.9065	2.0943 **	0.8003	−1.1445	0.8441	0.9267	0.8821	0.3895
16	0.9656	3.2811 ***	0.8505	0.0575	0.8948	1.9619 **	0.9161	1.3074 *

Table A2 presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 1 month-ahead out-of-sample forecast for the full sample from 1995 M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The OLS estimation is performed using a rolling regression with 60 window size from 1995 M1 to 1999 M12 and the remaining sample for the out-of-sample forecast. For Norway, Chile and Mexico, the number of observations (T + 1) is 299, and the number of forecasts (P) is 239. However, due to the unavailability of data for New Zealand, (T + 1) = 274 and P = 214. R.MSFE above 1 indicates that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ***, ** and * show that the random walk is rejected at 1%, 5% and 10% significance level, respectively.

Table A3. Taylor rule fundamentals forecast until the financial crisis with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**
1	0.9130	0.8512	0.8389	−0.0752	1.0111	2.3596 ***	1.0087	1.9035 **
2	1.0129	1.8783 **	0.8536	−0.5864	0.9819	1.9450 **	1.0355	2.0877 **
3	0.9449	1.6752 **	0.7362	0.1460	0.9616	2.0835 **	0.9746	1.6280 *
4	0.8462	1.0371	0.6939	−0.1092	0.9352	1.8031 **	0.9606	0.8050
5	0.9354	0.7297	0.9147	−0.4414	1.0144	2.2626 **	0.9956	0.8469
6	1.0066	1.7160 **	0.9398	−0.6915	1.0465	2.8568 ***	1.0390	1.5825 *
7	0.9861	2.3374 ***	0.7856	−1.2723	1.0178	1.8237 **	1.0109	1.8679 **
8	0.9010	1.1180	0.7763	−0.9972	0.9571	2.0061 **	0.9705	0.6645
9	0.8530	−0.6033	0.9342	−0.0923	0.9407	1.4517 *	1.0245	1.1560
10	0.9139	0.8741	0.8406	−0.0605	0.9853	2.1143 **	1.0100	1.9186 **
11	0.9389	1.1637	0.7254	−1.1851	0.8903	1.2233	0.9328	0.6491
12	0.9793	1.8889 **	0.7406	0.1703	0.8890	1.4653 *	0.9842	1.7114 **
13	0.9159	0.0625	0.8477	−1.5401	0.9282	0.4731	0.9871	0.3743
14	0.9361	0.7205	0.9142	−0.4438	1.0163	2.2849 **	0.9961	0.8554
15	0.9638	1.4798 *	0.7407	−2.4105	0.9787	1.3009 *	1.0178	1.0772
16	0.9928	2.3920 ***	0.7864	−1.2923	0.9434	1.4581 *	1.0200	1.8680 **

This table presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West (CW) statistics for a 1 month-ahead out-of-sample forecast for the period until the financial crisis and the great recession. The sample covers from 1995 M1 to 2008 M12. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The OLS estimation is performed using a rolling regression with 60 window size from 1995 M1 to 1999 M12 and the remaining sample for the out-of-sample forecast. For Norway, Chile, New Zealand and Mexico, the number of observations (T + 1) is 168, and the number of forecasts (P) is 108. R.MSFE above 1 indicates that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ***, ** and * show that the random walk is rejected at 1%, 5% and 10% significance level, respectively.

Table A4. Taylor rule fundamentals forecast in the post-financial crisis with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**
1	0.8985	−0.0223	0.8684	−0.6357	0.9087	1.6652 **	0.9811	1.4600 *
2	0.8756	−0.9647	1.0034	0.9318	0.9215	−1.9769	0.8728	−1.0589
3	0.7832	0.5816	0.7355	−0.8177	1.1478	2.8820 ***	0.7222	0.4526
4	0.8367	0.0172	0.8238	−0.719	0.8205	0.6305	0.6978	−1.7000
5	0.9562	0.5537	0.9890	0.6090	0.9158	−1.6638	0.9187	−0.1533
6	0.9629	−0.9979	1.0016	0.9312	0.9553	−0.7282	0.9290	−1.083
7	0.8754	−0.1025	0.9388	−0.3689	0.8219	−1.4401	0.9228	0.7682
8	0.9059	0.4585	0.9470	−0.2228	0.9272	−0.0414	0.8678	−2.6233
9	0.7626	−0.5391	0.8774	−0.6870	0.7730	0.6323	0.8473	0.2281
10	0.9004	0.1153	0.8720	−0.6895	0.8014	−0.1290	0.9733	1.3052 *
11	0.7272	−0.3102	0.7325	-0.5015	0.9318	1.8273 **	0.6055	0.1523
12	0.7873	0.6003	0.7391	−0.8850	0.8374	1.2645	0.6898	0.4658
13	0.8285	−0.0407	0.8794	−0.2763	0.7878	−2.2377	0.8658	−0.3735
14	0.9530	0.5297	0.9879	0.5823	0.9245	−1.4380	0.9172	−0.1245
15	0.8084	−0.1346	0.8172	−0.5581	0.6991	−2.2012	0.8026	−0.5160
16	0.8670	−0.1669	0.9365	−0.4199	0.8463	−1.1448	0.9185	0.6142

This table reports the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 1 month-ahead out-of-sample forecast for the period after the financial crisis. The sample runs from 2009 M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The OLS estimation is performed using a rolling regression with 60 window size from 2009 M1 to 2013 M12 and the remaining sample for the out-of-sample forecast. For Norway, Chile and Mexico, the number of observations (T + 1) is 131, and the number of forecasts (P) is 71. However, due to the unavailability of data for New Zealand, (T + 1) = 106 and P = 46. R.MSFE above 1 indicates that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ***, ** and * show that the random walk is rejected at 1%, 5% and 10% significance level, respectively.

Table A5. Two months-ahead forecasts using Taylor rule fundamentals with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**
1	0.8095	−0.9226	0.7973	−1.0027	0.9152	1.7413 **	0.8888	0.5754
2	0.8692	−0.0550	0.8420	−1.2095	0.8583	−0.2475	0.8922	−0.6344
3	0.7399	1.0431	0.6466	−0.1134	0.7361	1.9249 **	0.6468	−0.8145
4	0.7056	−0.9817	0.6342	−1.3666	0.7275	0.0013	0.7016	−2.4359
5	0.8601	−0.5850	0.9169	−1.0181	0.8989	−0.1538	0.8972	−0.6623
6	0.9354	0.3380	0.9394	−1.1774	0.9388	0.4637	0.9300	−0.7510
7	0.8710	1.7787 **	0.7573	−1.0310	0.8217	0.6960	0.8389	−0.3220
8	0.7893	−1.0326	0.7677	−1.4836	0.7995	0.0367	0.8543	−1.7698
9	0.7268	−2.5201	0.7641	−0.4412	0.8270	0.4461	0.8469	0.1555
10	0.8095	−0.8510	0.7998	−0.9923	0.8392	0.9762	0.8875	0.5153
11	0.6732	0.2553	0.5868	−0.4163	0.6428	1.0762	0.5635	−1.2967
12	0.7526	1.2942 *	0.6519	−0.0551	0.6598	0.5047	0.6255	−0.7125
13	0.7938	−1.7760	0.8391	−1.2078	0.8034	−1.8932	0.8677	−0.8523
14	0.8615	−0.5556	0.9164	−1.0272	0.9000	−0.1150	0.8968	−0.6373
15	0.7857	1.0447	0.7010	−1.3586	0.7087	−0.3285	0.7921	−1.4813
16	0.8728	1.8382 **	0.7587	−1.0201	0.7782	0.4674	0.8404	−0.3776

This table presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 2 months-ahead out-of-sample forecast for the full sample from 1995 M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The estimation is performed using a rolling regression with 60 window size from 1995 M1 to 1999 M12 and the remaining sample for the out-of-sample forecast. The serial correlation is checked using the Newey–West estimator with lag 4. For Norway, Chile and Mexico, the number of observations (T + 1) is 299, and the number of forecasts (P) is 239. However, due to the unavailability of data for New Zealand, (T + 1) = 274 and P = 214. R.MSFE above 1 indicates that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ** and * show that the random walk is rejected at 5% and 10% significance level, respectively.

Table A6. Three months-ahead forecasts using Taylor rule fundamentals with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**
1	0.7936	−1.0581	0.7825	−0.9523	0.8749	1.2196	0.9050	1.2010
2	0.8558	−0.3015	0.8308	−1.1224	0.8181	−0.8687	0.9050	−0.2514
3	0.7061	0.6939	0.5964	−0.0274	0.6735	1.9382 **	0.6213	0.1006
4	0.6741	−1.2309	0.5927	−1.3343	0.6825	−0.3268	0.7119	−1.6080
5	0.8400	−0.8240	0.9112	−1.1327	0.8695	−0.6967	0.9062	−0.3429
6	0.9278	0.2569	0.9366	−1.2529	0.9185	0.0806	0.9372	−0.4941
7	0.8426	1.4340 *	0.7316	−1.1514	0.7888	0.3984	0.8457	0.1092
8	0.7664	−1.1463	0.7419	−1.6913	0.7639	−0.1768	0.8774	−1.2281
9	0.7011	−2.3364	0.7799	0.3491	0.7788	−0.2020	0.8672	1.2043
10	0.7932	−0.9875	0.7876	−0.9218	0.7909	0.3491	0.9043	1.1360
11	0.6040	0.0915	0.5238	−0.3922	0.5386	0.7354	0.5170	−0.1280
12	0.7165	0.9625	0.6044	0.0806	0.5860	−0.0114	0.5910	0.1893
13	0.7667	−1.7693	0.8304	−1.1784	0.7675	−2.0489	0.8869	0.1127
14	0.8420	−0.7888	0.9103	−1.1429	0.8705	−0.6441	0.9065	−0.3069
15	0.7315	0.7575	0.6639	−1.1044	0.6324	−0.7536	0.8108	−0.1792
16	0.8440	1.5029 *	0.7320	−1.1299	0.7409	0.1582	0.8487	0.1066

This table presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 3 months-ahead out-of-sample forecast for the full sample from 1995 M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The estimation is performed using a rolling regression with 60 window size from 1995 M1 to 1999 M12 and the remaining sample for the out-of-sample forecast. The serial correlation is checked using the Newey–West estimator with lag 4. For Norway, Chile and Mexico, the number of observations (T + 1) is 299, and the number of forecasts (P) is 239. However, due to the unavailability of data for New Zealand, (T + 1) = 274 and P = 214. R.MSFE above 1 indicate that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ** and * show that the random walk is rejected at 5% and 10% significance level, respectively.

Table A7. Directional accuracy test using Taylor rule fundamentals with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy
1	0.3523	51.05%	0.4806	50.21%	0.0020	59.81% ***	0.0255	55.65% **
2	0.7992	47.28%	0.4813	50.21%	0.1592	53.27%	0.4249	50.63%
3	0.6699	48.54%	0.4226	50.63%	0.0002	62.15% ***	0.0080	57.74% ***
4	0.1386	53.56%	0.5817	49.37%	0.1364	53.74%	0.3751	51.05%
5	0.1384	5356%	0.5282	49.79%	0.1782	53.27%	0.5926	49.37%
6	0.4239	50.63%	0.4753	50.21%	0.0341	56.07% **	0.8404	46.86%
7	0.1827	52.72%	0.2380	52.30%	0.0728	55.14% *	0.1356	53.56%
8	0.2877	51.88%	0.6927	48.54%	0.0499	55.61% **	0.8918	46.03%
9	0.8882	46.03%	0.9455	45.19%	0.1439	53.74%	0.5375	49.79%
10	0.4021	50.63%	0.4803	50.21%	0.0730	55.14% *	0.0487	54.81% **
11	0.7288	48.12%	0.5223	49.79%	0.0014	60.28% ***	0.7269	48.12%
12	0.5153	49.79%	0.3247	51.46%	0.0012	60.28% ***	0.0080	57.74% ***
13	0.2355	52.30%	0.9329	45.19%	0.4155	50.47%	0.5948	49.37
14	0.0889	54.39% *	0.5277	49.79%	0.1732	53.27%	0.5382	49.79%
15	0.3105	51.46%	0.7996	47.28%	0.0096	57.94% ***	0.5783	49.37%
16	0.1521	53.14%	0.1655	53.14%	0.0056	58.41% ***	0.2001	52.72%

The table reports the directional accuracy which explains the percentage change of the exchange rates that were accurately forecasted with the Taylor rule fundamentals. The directional accuracy is tested after performing the 1 month-ahead out-of-sample forecast for the full sample from 1995M1 to 2019M11. The window size used is 60. PT-test is used in this table. The null hypothesis is that the actual and forecasted exchange rate values are independently distributed. The columns are directional accuracy and the *p*-values of the PT-test. ***, ** and * indicate that the null hypothesis is rejected at 99%, 95% and 90% confidence interval, respectively.

Table A8. Directional accuracy test until the financial crisis with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy
1	0.2261	53.70%	0.2268	53.70%	0.0060	62.04% ***	0.0214	57.41% **
2	0.8498	45.37%	0.5888	49.07%	0.0271	59.26% **	0.0873	56.48% *
3	0.5767	49.07%	0.2268	53.70%	0.0167	60.19% **	0.0319	58.33% **
4	0.2252	53.70%	0.3683	51.85%	0.1263	55.56%	0.2725	52.78%
5	0.1263	55.56%	0.4387	50.93%	0.0169	60.19% **	0.4637	50.00%
6	0.1713	54.63%	0.5014	50.00%	0.0004	65.74% ***	0.7102	47.22%
7	0.0857	56.48% *	0.6683	48.15%	0.0414	58.33% **	0.1626	54.63%
8	0.2268	53.70%	0.4434	50.93%	0.0056	62.04% ***	0.8898	44.44%
9	0.8303	45.37%	0.9375	43.52%	0.0947	55.56% *	0.4556	50.00%
10	0.2261	53.70%	0.2268	53.70%	0.0580	57.41% *	0.0214	57.41% **
11	0.3828	50.93%	0.5856	49.07%	0.1160	55.56%	0.9162	43.52%
12	0.3576	51.85%	0.2269	53.70%	0.0417	58.33% **	0.0319	58.33% **
13	0.2269	53.70%	0.9701	41.67%	0.1204	55.56%	0.7094	47.22%
14	0.0624	57.41% *	0.4387	50.93%	0.0418	58.33% **	0.5499	49.07%
15	0.2916	52.78%	0.9522	42.59%	0.0019	63.89% ***	0.7748	46.30%
16	0.0873	56.48% *	0.5922	49.07%	0.0091	61.11% ***	0.2134	53.70%

This table presents the directional accuracy which explains the percentage change of the exchange rates that were accurately forecasted with the Taylor rule fundamentals. The directional accuracy is tested after performing the 1 month-ahead out-of-sample forecast for the sample until the financial crisis from 1995M1 to 2008M12. The window size used is 60. PT-test is used in this table. The null hypothesis is that the actual and forecasted exchange rate values are independently distributed. The columns are directional accuracy and the *p*-values of the PT-test. ***, ** and * indicate that the null hypothesis is rejected at 99%, 95% and 90% confidence interval, respectively.

Table A9. Directional accuracy test in the post-financial crisis with 60 window size.

Model	Norway		Chile		New Zealand		Mexico	
	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy
1	0.4667	49.30%	0.6811	47.89%	0.0173	63.04% **	0.0639	60.56% *
2	0.5559	47.89%	0.3563	53.52%	0.5000	50.00%	0.9813	40.85%
3	0.7539	46.48%	0.8370	43.66%	0.0159	65.22% **	0.5356	52.11%
4	0.4946	50.70%	0.6275	46.48%	0.1303	56.52%	0.9347	42.25%
5	0.2478	56.34%	0.8019	47.89%	0.5732	47.83%	0.7506	47.89%
6	0.8584	45.07%	0.3248	53.52%	0.7525	45.65%	0.9813	40.85%
7	0.9011	43.66%	0.2360	54.93%	0.4408	47.83%	0.3092	53.52%
8	0.8219	46.48%	0.4079	52.11%	0.1930	54.35%	0.9041	43.66%
9	0.6879	45.07%	0.6098	47.89%	0.1629	52.17%	0.2738	54.93%
10	0.5559	47.89%	0.6630	47.89%	0.1930	54.35%	0.1567	57.75%
11	0.9168	42.25%	0.2145	50.70%	0.0031	67.39% ***	0.7506	47.89%
12	0.7539	46.48%	0.7768	45.07%	0.0510	60.57% *	0.3304	54.93%
13	0.2740	54.93%	0.3227	47.89%	0.6032	47.83%	0.7315	49.30%
14	0.2478	56.34%	0.8589	46.48%	0.3668	52.17%	0.5964	50.70%
15	0.5808	49.30%	0.3227	47.89%	0.6096	43.48%	0.4702	50.70%
16	0.8442	45.07%	0.2360	54.93%	0.2022	52.17%	0.2887	53.52%

This table presents the directional accuracy which explains the percentage change of the exchange rates that were accurately forecasted with the Taylor rule fundamentals. The directional accuracy is tested after performing the 1 month-ahead out-of-sample forecast for the sample after the financial crisis from 2009M1 to 2019M11. The window size used is 60. PT-test is used in this table. The null hypothesis is that the actual and forecasted exchange rate values are independently distributed. The columns are directional accuracy and the *p*-values of the PT-test. ***, ** and * indicate that the null hypothesis is rejected at 99%, 95% and 90% confidence interval, respectively.

Appendix D. Out-of-Sample Forecast with 120 Window Size

Table A10. One month-ahead forecasts using Taylor rule fundamentals with 120 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat
1	0.9063	−2.0031	0.9592	−0.2488	0.8771	0.3452	0.9543	0.0799
2	0.9444	−1.8616	0.9742	−0.1443	0.9334	−0.2917	0.9562	−0.3261
3	0.9779	2.1202 **	0.9303	0.8035	0.8851	1.5198 *	0.8611	−0.5517
4	0.9463	1.6581 **	0.9124	−0.2047	0.9175	1.0503	0.9053	0.0158
5	0.9294	−2.0619	0.9740	−0.3223	0.9476	0.0666	0.9709	0.2446
6	0.9396	−2.3887	0.9838	−0.0265	0.9611	0.2315	0.9655	−1.2765
7	0.9906	2.2043 **	0.9476	0.5955	0.9115	1.5477 *	0.8872	−1.8763
8	0.9533	0.2775	0.9624	−0.1645	0.9382	0.3376	0.9457	−0.5228
9	0.9031	−2.1569	0.9453	−0.0644	0.8608	−0.1151	0.9122	−1.2996
10	0.9082	−1.9923	0.9590	−0.2339	0.8742	−0.2544	0.9523	0.0339
11	0.9378	1.9324 **	0.9175	0.7506	0.8527	1.0948	0.8450	−0.7142
12	0.9784	2.0693 **	0.9307	0.8029	0.8682	0.6805	0.8576	−0.6301
13	0.8877	−2.8950	0.9661	−0.2035	0.9276	−0.3192	0.9403	−0.8985
14	0.9295	−2.0453	0.9740	−0.3240	0.9399	−0.0676	0.9681	0.2120
15	0.9473	1.5808 *	0.9288	0.1818	0.8782	1.0077	0.8608	−2.2444
16	0.9948	2.0611 **	0.9492	0.6005	0.8837	1.0024	0.8807	−1.9585

Note: This table presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 1 month-ahead out-of-sample forecast for the full sample from 1995 M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The OLS estimation is performed using a rolling regression with 120 window size from 1995 M1 to 2004 M12 and the remaining sample for the out-of-sample forecast. This is done to check the window sensitivity effect on the forecast. For Norway, Chile and Mexico, the number of observations (T + 1) is 299, and the number of forecasts (P) is 179. However, due to the unavailability of data for New Zealand, (T + 1) = 274 and P = 154. R.MSFE above 1 indicate that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ** and * show that the random walk is rejected at 5% and 10% significance level, respectively.

Table A11. Taylor rule fundamentals forecast until the financial crisis with 120 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**
1	0.8852	−2.0073	0.9418	−0.4307	0.8785	−1.1306	0.9697	0.6728
2	0.9099	−1.9923	0.9509	−0.3719	0.8878	−0.9423	0.9735	0.0772
3	1.0900	1.3703 *	0.8952	−0.0084	0.8971	−0.0339	0.9965	1.3638 *
4	0.9816	0.7211	0.8286	−0.7747	0.9041	−0.0054	1.0485	1.7695 **
5	0.9075	−1.7657	0.9428	−0.4945	0.9344	−0.3158	1.0263	1.4759 *
6	0.9231	−1.8502	0.9483	−0.3994	0.9731	0.3959	1.0166	1.7695 **
7	1.1572	1.5436 *	0.9330	−0.2035	0.9471	0.3600	0.9512	−0.4345
8	0.9177	−0.8924	0.9009	−0.8425	0.8529	−1.2831	1.0251	1.4005 *
9	0.8898	−1.4926	0.9539	−0.4171	0.8592	−1.5545	0.9652	0.3590
10	0.8869	−2.0436	0.9425	−0.4210	0.8643	−1.4193	0.9688	0.6423
11	1.0983	1.0720	0.8996	0.0564	0.8881	−0.0162	0.9934	0.7555
12	1.1164	1.3685 *	0.8980	0.0147	0.9047	0.1239	0.9980	1.3315 *
13	0.9074	−1.4510	0.9572	−0.3681	0.9190	−0.3573	1.0176	0.8172
14	0.9084	−1.7872	0.9430	−0.4890	0.9214	−0.4453	1.0257	1.4806 *
15	1.1416	1.3313 *	0.9545	−0.0076	0.8691	−0.2929	0.9377	−1.1007
16	1.1768	1.5382 *	0.9381	−0.1377	0.8642	−1.0485	0.9536	−0.4134

This table presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West (CW) statistics for a 1 month-ahead out-of-sample forecast for the period until the financial crisis and the great recession. The sample covers from 1995 M1 to 2008 M12. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The OLS estimation is performed using a rolling regression with 120 window size from 1995 M1 to 2004 M12 and the remaining sample for the out-of-sample forecast. For Norway, Chile, New Zealand and Mexico, the number of observations (T + 1) is 168, and the number of forecasts (P) is 48. R.MSFE above 1 indicates that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ** and * show that the random walk is rejected at 5% and 10% significance level, respectively.

Table A12. Taylor rule fundamentals forecast in the post-financial crisis with 120 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**	**R.MSFE**	**T-Stat**
1	0.9873	0.2859	0.9888	0.1923	0.4821	−0.1519	1.0832	1.3836 *
2	0.8243	−1.3386	1.0631	2.0984 **	1.0249	0.9143	0.7852	−0.7178
3	0.5715	−1.3473	1.0213	0.9981	0.9444	0.5387	0.9334	0.2996
4	0.5528	−1.3412	0.9931	0.2134	0.5873	−0.4984	0.6344	−1.4861
5	0.9873	0.2171	1.0684	2.3011 **	1.0186	0.5244	0.7718	−0.6564
6	0.8874	−1.3408	1.0661	2.4418 ***	1.0263	0.9407	0.9806	−0.6138
7	0.9461	0.5983	1.0595	1.9601 **	0.9223	−0.2711	0.7155	−0.8690
8	0.9755	0.7698	1.0576	1.7816 **	0.9179	−0.3024	0.9627	−0.1872
9	1.0379	0.9937	0.9962	0.2962	0.4420	−0.1482	1.0545	1.0591
10	0.9887	0.3092	0.9869	0.1491	0.6625	−0.0935	1.0875	1.5015 *
11	0.4934	−1.2789	1.2106	2.5037 ***	1.1149	1.2577	0.7497	0.6434
12	0.5717	−1.3399	1.0245	1.0625	0.6338	−0.2372	0.9027	−0.2176
13	1.0379	0.8520	0.9898	0.1858	0.9805	0.2122	0.7788	−0.7543
14	0.9930	0.3341	1.0670	2.2501 **	1.0239	0.6777	0.7513	−0.6540
15	0.8756	−0.4526	1.0151	0.5896	0.8187	−0.4810	0.7079	−0.8501
16	0.9267	0.3508	1.0578	1.9536 **	0.9112	−0.3509	0.6714	−0.7914

This table reports the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 1 month-ahead out-of-sample forecast for the period after the financial crisis. The sample runs from 2009M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The OLS estimation is performed using a rolling regression with 120 window size from 2009M1 to 2018M12 and the remaining sample for the out-of-sample forecast. For Norway, Chile and Mexico, the number of observations (T + 1) is 131, and the number of forecasts (P) is 11. However, due to the unavailability of data for New Zealand, 96 window size is used for the rolling regression. (T + 1) = 106 and P = 10. R.MSFE above 1 indicate that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. ***, ** and * show that the random walk is rejected at 1%, 5% and 10% significance level, respectively.

Table A13. Two months-ahead forecasts using Taylor rule fundamentals with 120 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat
1	0.8803	−2.2716	0.9534	−0.3441	0.8392	−0.3273	0.9403	−0.3125
2	0.9276	−1.7871	0.9638	−0.4639	0.9014	−0.8334	0.9444	−0.6587
3	0.9232	1.2349	0.9038	0.4537	0.8160	0.3999	0.8258	−1.2834
4	0.8937	0.6735	0.8862	−0.4857	0.8492	0.0195	0.8785	−0.4377
5	0.9094	−2.2157	0.9604	−0.7320	0.9218	−0.5795	0.9646	0.0180
6	0.9289	−2.4494	0.9700	−0.4971	0.9404	−0.3609	0.9634	−1.3256
7	0.9497	1.4161 *	0.9193	−0.0666	0.8652	0.6480	0.8583	−2.3034
8	0.9189	−0.6074	0.9376	−0.7488	0.9009	−0.4585	0.9295	−0.9545
9	0.8589	−2.8561	0.9394	−0.0351	0.8209	−0.6857	0.8787	−1.7814
10	0.8831	−2.2473	0.9532	−0.3229	0.8373	−0.8153	0.9382	−0.3561
11	0.8721	1.1844	0.3881	0.2842	0.7758	0.0431	0.7959	−1.4531
12	0.9219	1.2620	0.9038	0.4536	0.7941	−0.4536	0.8212	−1.3982
13	0.8470	−3.1445	0.9565	−0.3710	0.8993	−0.9476	0.9168	−1.3938
14	0.9105	−2.2087	0.9604	−0.7318	0.9122	−0.7071	0.9619	−0.0051
15	0.8885	0.6817	0.8919	−0.4111	0.8279	0.2137	0.8143	−2.4786
16	0.9502	1.2829 *	0.9211	−0.0472	0.8426	0.2793	0.8506	−2.3818

This table presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 2 months-ahead out-of-sample forecast for the full sample from 1995 M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The estimation is performed using a rolling regression with 120 window size from 1995 M1 to 2004M12 and the remaining sample for the out-of-sample forecast. The serial correlation is checked using the Newey–West estimator with lag 4. For Norway, Chile and Mexico, the number of observations (T + 1) is 299, and the number of forecasts (P) is 179. However, due to the unavailability of data for New Zealand, (T + 1) = 274 and P = 154. R.MSFE above 1 indicate that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model. * shows that the random walk is rejected at 10% significance level, respectively.

Table A14. Three months-ahead forecasts using Taylor rule fundamentals with 120 window size.

Model	Norway		Chile		New Zealand		Mexico	
	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat	R.MSFE	T-Stat
1	0.8710	−2.4126	0.9616	−0.1370	0.8200	−0.6012	0.9443	−0.1471
2	0.9191	−1.9359	0.9733	−0.1804	0.8871	−1.0439	0.9480	−0.5165
3	0.8933	0.9542	0.8895	0.2959	0.7854	0.1078	0.8317	−0.8595
4	0.8675	0.2673	0.8793	−0.4550	0.8154	−0.2684	0.8855	−0.0686
5	0.9016	−2.4215	0.9645	−0.6893	0.9148	−0.8014	0.9712	0.2162
6	0.9244	−2.6400	0.9730	−0.4653	0.9351	−0.5786	0.9704	−0.8319
7	0.9252	1.2043	0.9144	−0.1315	0.8545	0.5759	0.8683	−2.0687
8	0.9047	−0.8939	0.9407	−0.5960	0.8999	−0.5462	0.9421	−0.5791
9	0.8379	−2.8230	0.9433	0.1731	0.8003	−0.8976	0.8864	−1.2824
10	0.8744	−2.3761	0.9614	−0.1168	0.8195	−1.0777	0.9424	−0.1968
11	0.8282	0.8312	0.8540	0.1699	0.7347	−0.3572	0.8020	−0.8008
12	0.8896	1.0079	0.8887	0.2882	0.7600	−0.8445	0.8275	−0.9585
13	0.8258	−3.0366	0.9561	−0.3502	0.8912	−1.0845	0.9307	−0.7334
14	0.9033	−2.4166	0.9644	−0.6922	0.9044	−0.9198	0.9689	0.1927
15	0.8485	0.3265	0.8777	−0.4391	0.8160	0.1595	0.8260	−2.0376
16	0.9224	1.0422	0.9155	−0.1209	0.8400	0.3093	0.8607	−2.1412

This table presents the relative mean squared forecast error (R.MSFE) and the test statistics of Clark and West statistics for a 3 months-ahead out-of-sample forecast for the full sample from 1995 M1 to 2019M11. The random walk without drift is used as the null hypothesis where the alternative hypothesis is a linear model with the Taylor rule fundamentals. The estimation is performed using a rolling regression with 120 window size from 1995 M1 to 2004 M12 and the remaining sample for the out-of-sample forecast. The serial correlation is checked using the Newey–West estimator with lag 4. For Norway, Chile and Mexico, the number of observations (T + 1) is 299, and the number of forecasts (P) is 179. However, due to the unavailability of data for New Zealand, (T + 1) = 274 and P = 154. R.MSFE above 1 indicates that the alternative model outperforms the random walk. CW is a standard normal with a one-sided test, and it tests the significance and accuracy of the alternative model.

Table A15. Directional accuracy test using Taylor rule fundamentals with 120 window size.

Model	Norway		Chile		New Zealand		Mexico	
	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy	PT *p*-Value	Directional Accuracy
1	0.9074	44.69%	0.8825	45.25%	0.0326	56.49% **	0.3370	51.40%
2	0.9755	42.46%	0.9228	44.13%	0.6281	48.70%	0.4035	50.84%
3	0.0514	55.31% *	0.2580	52.51%	0.0732	55.19% *	0.4065	50.84%
4	0.5083	50.84%	0.2527	51.40%	0.3117	51.95%	0.5851	49.16%
5	0.9749	42.46%	0.6633	48.04%	0.6286	48.70%	0.2730	51.96%
6	0.7720	46.93%	0.4321	50.28%	0.4340	50.65%	0.5845	49.16%
7	0.3912	50.84%	0.7515	47.49%	0.0894	55.19% *	0.9421	44.13%
8	0.9305	46.37%	0.9229	44.13	0.0328	57.14% **	0.5212	49.72%
9	0.9512	44.13%	0.5924	48.60%	0.4356	50.65%	0.6451	48.60%
10	0.8782	45.25%	0.8512	45.81%	0.2969	51.95%	0.3331	51.40%
11	0.0536	55.87% *	0.1431	54.19%	0.2470	52.60%	0.5888	49.16%
12	0.0744	54.75% *	0.2580	52.51%	0.1994	53.25%	0.4671	50.28%
13	0.9793	43.02%	0.7546	46.93%	0.5000	50.00%	0.5275	49.72%
14	0.9325	44.13%	0.7191	47.49%	0.4347	50.65%	0.3889	50.84%
15	0.0605	55.87% *	0.6883	48.60%	0.4335	50.65%	0.8427	46.37%
16	0.2773	51.96%	0.6477	48.60%	0.1952	53.25%	0.9225	44.69%

The table reports the directional accuracy which explains the percentage change of the exchange rates that were accurately forecasted with the Taylor rule fundamentals. The directional accuracy is tested after performing the 1 month-ahead out-of-sample forecast for the full sample from 1995M1 to 2019M11. The window size used is 120. PT-test is used in this table. The null hypothesis is that the actual and forecasted exchange rate values are independently distributed. The columns are directional accuracy and the *p*-values of the PT-test. ** and * indicate that the null hypothesis is rejected at 95% and 90% confidence interval, respectively.

Notes

1 This fact is supported by evidence reported by Bloomberg on 27 August 2019. https://www.bloomberg.com/news/articles/2019-08-26/norway-s-1-trillion-fund-weighs-pivotal-shift-to-u-s-stocks (accessed on 11 September 2020).

2 U.S. and Norway are part of the world's largest oil producers. Chile is among the world's copper producers. New Zealand provides about 50 percent of the world's export of lamb and mutton.

3 Diebold and Mariano (1995) and West (1996) (DMW tests) introduced tests for equal predictability for non-nested models.

4 $\pi_t^{\dagger}$ is positive since deflation could be more harmful to the economy than low inflation (Molodtsova and Papell 2009).

5 The foreign exchange rates are extracted from the Federal Reserve Bank of St. Louis database. The remaining data are taken from DataStream. Industrial Productions (IP) are used as the output, except New Zealand whose IP data index was only available in quarterly frequencies up to 2017 Q4. However, since the study works with monthly data, the Eviews 11 student version is used to convert the quarterly data to monthly frequencies which is available up to 2017M10.

6 A 14,400 smoothness parameter is applied for the HP filter since the data frequency is monthly.

7 Inflation rate (π_t): $\ln(\mathrm{CPI_t}) - \ln(\mathrm{CPI_{t-12}})$. Thus, the inflation rate is measured as the 12-month difference of the CPI.The lag of interest rate: $\mathrm{i_{t-1}}$Real exchange rate ($\mathrm{z_t}$): $\mathrm{s_t + p_t - p_t{}^*}$), $\mathrm{p_t}$ and $\mathrm{p_t{}^*}$ are the log $\mathrm{CPI_t}$ of the U.S and foreign countries.

8 In Cheung et al. (2019), though the Taylor rule fundamentals are evaluated to outperform the random walk, the null hypothesis of the random walk could not be rejected when the DMW test was applied.

9 We need to note that applying the test to the sub sample could change the stationarity result of the ADF test. In addition, due to country-specific data and target, it is more likely to see no stationarity which makes it difficult to interpret stationarity, but that is not the objective in this paper.

10 For Norway, Chile and Mexico, the number of observations (T + 1) is 299, and the number of forecasts (P) is 239. However, due to the unavailability of data for New Zealand, (T + 1) = 274 and P = 214.

11 Moura (2010) and Moura and de Moura and Carvalho (2010) tested the Taylor model predictability for the exchange rates in the Latin America and found a very low performance of the model in Chile and significant evidence in Mexico.

12 (T + 1) = 168 and P = 108 for Norway, Chile, New Zealand and Mexico.

13 Molodtsova and Papell (2012) use prescriptive Taylor rule models to investigate out-of-sample exchange rate forecasting at the time of the financial crisis. They found successive predictability of the USD/EUR exchange rate with the Taylor rule model during the financial crisis. Byrne et al. (2016) also find evidence of exchange rate predictability with the Taylor rule fundamentals at the financial crisis period.

14 As usual, 60 observations from the sample data are used for the estimation under a rolling window regression. One month-ahead out-of-sample forecast is performed for the remaining sample. CW statistics is used to test the forecast accuracy. Norway, Chile and Mexico, (T + 1) = 131 and P = 71. For New Zealand, (T + 1) = 106 and P = 46.

15 Clark and West (2006, 2007) recommend that a Newey–West estimator should be regressed on the $\hat{f}_{t+1}$ to make our forecast more robust. The Newey–West lag is computed as proposed by Newey and West (1987) as l_{nw} = floor $[4(P/100)^{2/9}]$. The Newey–West lag for Norway, Chile and Mexico is l_{nw} = floor [4.8545] = 4. For New Zealand, l_{nw} = floor [4.7368] = 4.

16 Ince (2014) uses real-time data to check the exchange rate forecast with the Taylor rule fundamentals for the U.S. with nine OECD countries and found that the Taylor rule fundamentals do not perform well in the long horizon.

17 Models 9 and 13 and models 2, 5, 6, 11 and 14 with the evaluation concept outperformed the random walk for Norway and New Zealand, respectively, but they are not significant with the CW statistics.

18 This could be biased since a very small sample of data was left for the out-of-sample forecast.

19 Molodtsova and Papell (2012) examined the USD/EUR exchange rate during the financial crisis and found that the Taylor rule fundamental could still predict the exchange. Ince et al. (2016) also proved the predictability of the Taylor rule fundamentals during the financial crisis and the great recession for eight countries.

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Article

The Twin Deficit Hypothesis in the MENA Region: Do Geopolitics Matter?

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Abstract: This paper examines the relationship between fiscal and external balances in MENA oil versus non-oil countries in the context of the twin deficits hypothesis (TDH) using Panel Vector Autoregression- Generalized Methods of Moments PVAR GMM estimation, Granger Causality and IRFs. The essence of this analysis is to assess the vulnerability of fiscal and external balances to oil price dynamics and regional geopolitics in the region. Results show that a twin-deficit problem exists in MENA oil-rich countries only while the problem does not exist in non-oil ones. This affirms the hypothesis that oil dependence results in high fiscal vulnerability to geopolitical shocks that automatically transmits to external balances. While a TDH isn't proven to exist in non-oil countries, fiscal and external balances problems result from longstanding structural factors. A high reliance on tourism revenues and remittances as main sources of foreign currency receipts (together with poor tax administration and enlarged current spending bills) makes those countries more vulnerable to domestic and external shocks; reflected in both growing fiscal and current account deficits. A large imports sector and relatively poor exporting capacity also contribute to weakening external accounts. The main policy recommendations for MENA oil-rich countries rely in the importance of strengthening the non-oil sector in order to diversify domestic sources of revenues. Adopting flexible exchange rates is recommended to decrease the vulnerability of the external shocks to oil price dynamics. For non-oil MENA regions, fiscal consolidation, reforming current spending and strengthening tax administrations are crucial to improve fiscal performance. Export-led growth strategies and inclusive growth policies would also contribute to improving external accounts in the examined economies.

Keywords: twin deficit hypothesis; budget balance; current account balance; MENA region; oil countries; non-oil countries; PVAR modeling

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1. Introduction

The relation between fiscal and current account balances has been proposed in contemporary economic theory and examined widely in empirical literature under the commonly known term "twin deficit hypothesis (TDH)". According to the Keynesian proposition, budget deficit (BD) has an impact on current account deficit (CAD) through the absorption theory, where an expansionary fiscal policy would expand the aggregate demand and the domestic absorption for imports in the economy which will worsen the current account deficit (CAD) (Abell 1990). Budget deficit affects the economy through high interest rates, low savings and low economic growth. This hypothesis constituted the basis for the Mundell–Fleming framework (Nargelecekenlera and Giray 2013). The TDH has been widely examined in literature, and different results exist relative to the presence and the direction of the relation between budget deficit and current account deficit. The twin deficit hypothesis is particularly relevant to the MENA region characterized by identified fiscal and monetary problems, resulting either from structural reasons or from the oil-based structures in some of those countries. In this paper, we investigate the twin deficit hypothesis in the MENA region by empirically examining the relation between fiscal balance and external account balance in 10 MENA countries. We group the sample countries into two groups: oil countries versus non-oil countries. This distinction is essential, as the MENA region has been affected by many factors in the past decades (such as oil prices, economic structure and state policies (Aristovnik 2007). Moreover, some MENA region countries already suffer from longstanding fiscal deficit and accumulated debt as well as poor external balance. We cover the period spanning from 1990s–2018 where most of the sample countries started structural economic reforms and adjustments programs after the 1970s oil crises and the Arab–Israeli war. The remainder of the paper is organized as follows: section two briefs the twin deficit hypothesis in theory and reviews some relevant literature. In section three, we present the analysis of the TDH in both oil and non-oil MENA countries using empirical methods and descriptive analysis. Finally, section four concludes and states some policy recommendations.

2. The Twin Deficit Hypothesis Resource-Rich Economies: Theory and Literature

The TDH was originally examined by Milne (1977), where he found that there exists a positive relation between the two deficits using a simple single equation model where budget deficit was found to affect current account deficit. More recent works involved rather advanced regression tools such as vector autoregressive models (VAR) (used in Abell (1990) and Enders and Lee (1990), who examined the TDH in the U.S. economy and came up with mixed findings on the existence of TDH in the U.S. economy). The main arguments related to the twin deficit are the (1) Keynesian proposition, which is a proponent to the twin convergence where the budget deficit causes the current account deficit and the (2) Ricardian equivalence hypothesis (REH), which supports the twin divergence where there is no link between the two deficits.

The Keynesian proposition—later employed in the Mundell–Fleming framework—relies on the notion that, in an open economy with a flexible exchange rate that depends on domestic borrowings to finance its debts, an increase in its budget deficit results in increased domestic interest rates (which consequently encourages foreign investors to invest in the home country). This results in higher capital inflows and an appreciation of the exchange rate that result from increased demand for financial assets in the country, which consequently increases demand for the home currency (Sakyi and Opoku 2016). As a result, exports decrease and imports increase, which creates the current account deficit. Hence, an increased budget deficit results in an increase in the current account deficit, which has been later referred to as the 'twin deficit hypothesis'. On the other hand, the Ricardian equivalence hypothesis refutes the twin deficit hypothesis based on the argument that expansionary fiscal policy does not affect consumption and output. Budget deficit arises from tax cuts that reduce public revenues where the public expenditures are assumed to be constant. Rational households tend to save the additional income they receive as a precautionary action towards the expectations of future government contractionary policies (such as raising taxes). Thus, an expansionary policy will result in high private savings and low government saving equivalently, and at the end there will be no impact on real interest rate, exchange rate or current account balance (Abbas et al. 2011). If the equivalence between the private savings and public savings didn't occur, then either a reduction in domestic investment or an increase in the current account deficit (or both) might occur (Helmy and Zaki 2017).

The literature employed different methods to analyze and investigate the TDH. A recent study by Kim and Roubini (2008) based on VAR models examined the effect of budget deficit shocks on the current account and the real exchange rate with a flexible exchange rate system in the US from 1973 to 2004 (post Bretton–Woods). They concluded that the presence of a twin divergence at an expansionary fiscal policy shock improved the current account and depreciated the real exchange rate. Rault and Afonso (2009) used bootstrap panel cointegration techniques and SUR methods to test for two balances (the BB and the CAB) for different EU and OECD countries from 1970 to 2007. Their findings affirmed a positive effect of budget balance on the current account balance for several

EU countries like Austria, Belgium, Czech Republic, Ireland, Latvia and Malta (which supports the TDH). On the contrary, Finland, Italy, Spain and UK were found to have a negative relationship between the BB and the CAB, thus rejecting the TDH. Furthermore, Vamvoukas (1999) tested the TDH from 1948 to 1994 in Greece and found short-run and long-run positive and significant causal link between budget deficit and current account deficit through co-integration and error correction modeling (ECM), thus affirming the Keynesian proposition. Conversely, later studies on Greece tested by Kalou and Paleologou (2012) from 1960 to 2007 and Nikiforos et al. (2015) from 1980 to 2010 applied a granger causality test and found the causality running from current account deficit to budget deficit, which proves the current account target hypothesis (thus refusing the TDH).

A number of papers examined the TDH resource-rich countries' single country models. and the results were mixed. For example, Alkswani (2000) examined the TDH in Saudi Arabia using Granger causality tests and found that there was a bidirectional causality, thus negating the presence of a TDH. Merza et al. (2012) found a negative long-run relationship between fiscal and external balances in Kuwait using VAR analysis; that is, an increase in the current account surplus will cause a budget deficit (which is opposite of the TDH). Marinheiro (2008) tested the relationship between the two deficits in Egypt and found that there is a positive relationship between the two balances. TDH was rejected due to reverse Granger causality running from current account deficit to budget deficit. Helmy (2018) used the same methodology for Egypt and found that there is a short-run reverse causation between current account deficit and budget deficit in favor of the current account targeting hypothesis. In other words, trade balance improves fiscal balance in the Egyptian economy. Bagheri et al. (2012) analyzed the Iranian economy (Iran being an oil-dependent economy). Using Johansen co-integration and Granger causality covering the period of 1971–2007, the paper found that a TDH holds as a result of fiscal policy ineffectiveness during business cycles. Neaime (2015) examined the same hypothesis in Lebanon from 1970 to 2013 and concluded that budget deficit has a significant impact on current deficit in the short run and referred to the significant impact of the fixed exchange rate regime in amplifying this relation together with the high interest rates and the low national savings, which, altogether, affected the current account. This is in addition to other structural factors such as inefficient government spending and revenue policies as well as corruption.

A limited number of studies attempted to assess the twin deficit hypothesis in resource-rich countries through panel analysis. Eldemerdash et al. (2014) tested the relationship between the current account and the fiscal balance of Arab small open developing countries with fixed exchange rate systems using ordinary least square fixed effects (OLSFE) and Granger causality tests. The findings supported the Keynesian view of a positive relationship between fiscal and external balances for oil-based countries. Similarly, Akanbi and Sbia (2018) investigated the TDH with respect to a panel of 31 oil exporting countries in the period between 1984 and 2013 through a two-stage least squares models. They concluded that TDH is not found in oil exporting countries, as the oil sector is blurring its existence.

3. Geopolitics, Oil-Price Shocks and Twin Deficits in MENA Region: An Empirical Investigation

In this paper, we contribute to the above literature on TDH through examining the twin deficit hypothesis in 10 MENA countries classified as being oil or non-oil economies. The classification of the examined MENA region economies as being oil or non-oil is done with the aim of examining the impact oil dependency as a source of domestic revenues and for foreign currency in making those economies' fiscal and external accounts more vulnerable to regional geopolitical shocks that transmit through oil price dynamics. We propose two research questions:

- Does a twin deficit hypothesis hold in MENA region countries?
- To what extent is the TDH related to geopolitical factors and oil-price related shocks?

The oil-rich countries included in our analysis are the UAE, Saudi Arabia, Kuwait, Iran and Libya, as they are the top oil exporting countries in the MENA and the world.

The non-oil countries are Egypt, Tunisia, Jordan, Morocco and Yemen. The period from 1990–2018 was chosen as it was the year of economic reforms and structural adjustments being implemented in most MENA countries. In the remainder of this section, we present some descriptive and statistical analysis as a preliminary illustration of the TDH in the MENA region and its possible relevance to geopolitical and oil-related shocks, both in oil and non-oil countries. This will be followed by an empirical examination of the same hypothesis using PVAR analysis, as will be explained thoroughly in the next section.

3.1. Descriptive Analysis

Primarily, an initial illustration of the budget balance and current account trends in oil-rich MENA countries (Figure 1) from 1990 to 2018 might demonstrate the presence of TDH in the examined countries. This is revealed by consistent periods of deficits and surpluses in both accounts. An intuitive interpretation of this result is that fiscal and monetary balances in such countries (being oil dependent) are most vulnerable to global and regional oil price shocks. A positive oil price shock results in surpluses in both balances and vice versa. Table 1 summarizes specific periods of significant oil prices shocks and the relevant impact on both budget balance and current account balance in the examined countries.

Figure 1. Budget deficit and current account deficit in oil-rich MENA countries (1990–2018). Source: IMF World Economic Outlook.

Table 1. Illustration of the relevance of main oil price shocks and events to the budget balance and current account balance in oil-rich MENA countries.

Country	Period	Oil Price Trends	Impact on Budget Balance and Current Account
Saudi Arabia	1990 to 2002	Low oils $20 per barrel. Asian financial crisis resulted in lower demand on oil globally.	Budget deficit of −0.9% to −5.9%. Current account deficit ranging between −3.7% and −8.9% and it reached −20.8% in 1995.
	2003–2013	Increase in oil prices from $31 per barrel to $98 per barrel. Iraq's war in 2003 which led to a decrease in oil production (Eid 2015).	Continuous budget surplus (1.2–5.6 percent of GDP) with a peak in 2008 of 29.8 percent of GDP in 2003. A surplus in current account balance (7.6–9.8 percent of GDP) with a peak of 27.4 percent in 2004. (IMF 2013b).
Kuwait	2005–2012		Budget balance reached 43.3 percent of the GDP in 2005. The current account balance reached 45.5 percent of GDP in the same year. The economy is relatively less oil-dependent and it has other diversified sources of revenues (such as VAT).
	1990–1993	War with Iraq resulted in the lowest level of oil production and revenues	In 1991, both balances witnessed a huge deficit of −151.3% of GDP in the budget balance and −242.2% of GDP in the current account balance (IMF 2005).
	1990–1998	War with Iraq resulted in a decrease in oil revenues that accounted for more than 70% of Iranian exports and more than 50% of government revenues (IMF 2000).	Budget deficit ranging from −2.1 to 6.1 percent of GDP. Current account deficit ranging from −0.5 to 6.5 percent of GDP, including a sharp deficit of −14.8 percent in 1992.
Iran	1999/2000	Positive oil price shock.	Surplus in both balances. Current account balance is 2.4 percent of GDP and budget surplus reached 6.6 percent of GDP in the same period
Libya	1999–2010	Rising oil prices and increased oil revenues.	Budget surpluses during this period and it reached 32.5 percent of GDP in 2008. Current account surpluses during this period and it reached 51.1 percent of GDP in 2006.
	2014–2016	Decrease in oil revenues	Budget deficit reaching −113.3 percent of GDP in 2016. Current account deficit was −78.4% in 2014 (World Bank 2017).

If one argues that oil dependency is a core factor causing the TDH in MENA oil region countries, then it would be expected that other non-oil dependent MENA economies would show a less prevalent twin deficit hypothesis. Nevertheless, the initial demonstration of budget balances and current account balances in those countries show different results. Twin deficits might occur in those countries due to structural fiscal imbalances as well as the high dependence on vulnerable sources of foreign currencies to finance external accounts. Such economies suffer from accumulated deficits during most of the studied period due to their dependence on other sources such as tourism, foreign aid, remittances and the adoption of pro-cyclical policies during recessions (Figure 2). Structural fiscal deficits persist due to the increased spending on subsidies and debt service. Deficits in current accounts result from poor export-driven growth, vulnerability of tourism and remittances revenues, as well as the high dependence on imported goods.

Figure 2. Budget deficit and current account deficit in non-oil MENA countries (1990–2018). Source: IMF World Economic Outlook.

Egypt, like all non-oil countries, is an economy that has these issues. In 1998, both balances were in deficit, having a −5.1% in the budget balance and −2.8% in the current account balance. The current account balance was affected this year as appreciation of the real exchange affected the competiveness of the exports and beside that the Luxor massacre in 1997 decreased tourism. In addition to the downturn in oil prices in the gulf area, exports and remittances also saw a downturn. This has also reflected on budget balance due to decreased revenue (Panizza 2001). Similarly, high dependence on remittances of Jordan and Yemen made them highly vulnerable to regional geopolitical shocks such as the Gulf wars and fluctuating oil prices. For example, the 1990 Gulf war worsened the situation, which lead to decreased foreign grants and the return home of Jordanian workers, which widened the deficit in both balances (Ramachandran 2004). Additionally, Yemen's support for Iraq from 1990 to 1991 during the Gulf war created deficits in both balances, where the war increased the government spending. The current account balance was also affected in 1993 as a result of the expulsion of one million Yemeni workers working in Saudi Arabia, impacting the remittances severely. This is in addition the cut in the economic aid from Saudi Arabia and Kuwait (Library of Congress–Federal Research Division 2008).

Following the Global Financial Crisis and the Arab Spring, non-oil economies witnessed a severe deterioration in both balances as depicted in Figure 3. The pro-cyclical fiscal policy adopted in those countries magnified the fiscal and external balance problems (Helmy and Zaki 2017). Politically-driven fiscal interventions worsened the fiscal performance massively. The huge increase in government spending to calm down the uprising resulted in an increase in the wage bill, food and energy subsidies and social measures such as programs for youth unemployment in Egypt and Tunisia. Similarly, current balances in those countries was affected severely due to the turbulence in the economy and insecurity, resulting in lower tourism receipts (IMF 2012). Morocco was also affected in both balances during the same period as a result of the mentioned exogenous shocks that affected the fiscal and external balances of the Moroccan economy negatively. However, what made the economy overcome such a high deficit was the higher grants, non-tax revenue, the reduction in the subsidy bill by almost 2% of the GDP and the reduction of spending on wages by nearly a half percent of GDP, which resulted in improving the fiscal and external balances shortly after the shock. The less dependence on energy imports and the increased substitution of industrial goods that are imported by domestic production (IMF 2013a) contributed to quickly improving the external balance in addition to the sustained remittances position.

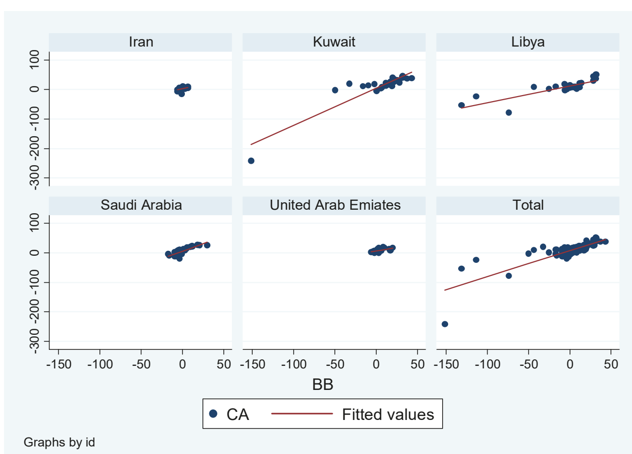

Figure 3. Correlation of budget balance with current account balance in oil-rich countries.

3.2. Modelling the TDH in MENA Countries: PVAR

We test the above hypothesis through Panel VAR (PVAR) tests through generalized impulse response functions (GIRF), cointegration and Granger causality tests to examine interactions between the current account balance, budget balance, real GDP growth and the other macro-fiscal variables as presented in Equation (1). Data descriptions are presented in Table 2.

$$CAB_{it} = \beta_0 + \beta_1 BB_{it} + \beta_2 REER_{it} + \beta_3 RGDP_{it} + \beta_4 INV + \beta_5 TO + U_{it} \quad (1)$$

Table 2. Data description and relevance to literature.

Variables	Description	Source	Relevance to Literature
CAB	Current account balance (surplus/deficit) as a % of GDP (in log)	IMF World Economic Outlook	The budget balance and current account balance are the main variables to be tested in the TDH. Rault and Afonso (2009) and Forte and Magazzino (2013) for EU countries, Eldemerdash et al. (2014) for oil and non-oil countries and Aloryito et al. (2016) for Sub-Saharan Africa.
BB	Net lending(+)/borrowing (-) (overall balance) as a % of GDP (in log)	IMF World Economic Outlook and World Bank	
REER	Real Effective Exchange rate (CPI based) (in log)	Bruegel working paper Darvas (2012)	Used in Aristovnik and Djurić (2010) and Forte and Magazzino (2013) for EU countries to show how this variable plays a pivotal role through how the budget balance affects the current account balance, which is similar to the Mundel–Flemming framework.
RGDP	Real GDP Growth as % of GDP (in log)	IMF World Economic Outlook	Real GDP growth is used because of the two balances having different responses to economic cycles that needs to be taken into consideration through this variable, which is shown in Eldemerdash et al. (2014) for oil and non-oil countries, Aloryito et al. (2016) for Sub-Saharan Africa and Akanbi and Sbia (2018) for oil exporting countries.
INV	Total investment as % of GDP (in log)	IMF World Economic Outlook	The total investment is mentioned in the national account identity explained earlier, which indicates that when there are investments, the current account balance worsens (which is used as a variable in Marinheiro (2008) and Helmy and Zaki (2017) for Egypt, Aristovnik and Djurić (2010) for EU countries, Anantha Ramu and Gayithri (2017) for india and Eldemerdash et al. (2014) for oil and non-oil countries).
TO	Trade openness as % of GDP (in log)	World bank and United Nations Statistics (UNCTAD stat)	Included to account for an economy's integration level, which will help in identifying the current account balance situation such as in Eldemerdash et al. (2014) for oil and non-oil countries and Akanbi and Sbia (2018) for oil exporting countries.

3.2.1. Correlation between Budget Balances and Current Account Balances in the MENA Region

Figures 3 and 4 present the correlation results between the budget balances and the current account balance in the examined countries. Figure 4 shows a strong positive correlation between the two balances. This is affirmed for independent countries and for all oil countries together. Oppositely, Figure 5 shows different results. A strong positive correlation only in Yemen while the correlation appears to be weaker in other countries.

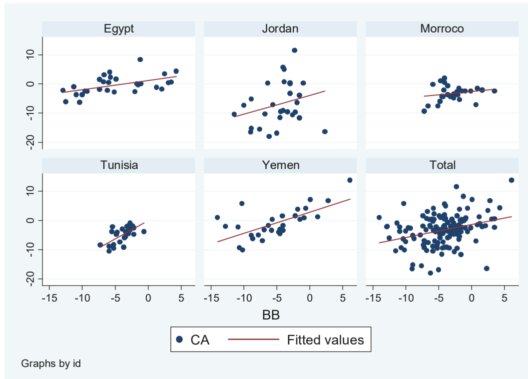

Figure 4. Correlation of budget balance with current account balance in non-oil countries.

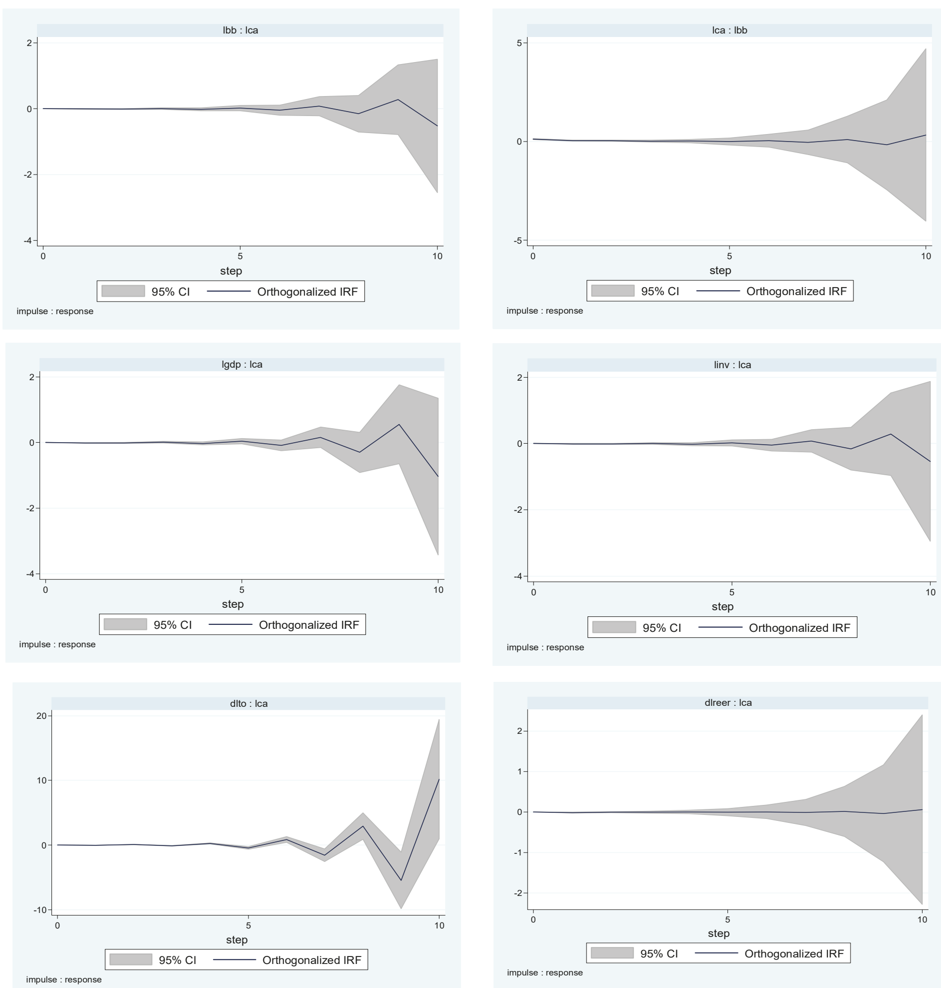

Figure 5. Impulse response functions (IRF) for oil-rich countries.

3.2.2. Panel Unit Root Tests and Cointegration Analysis

The stationarity of the variables is tested using Levin et al. (2002) (LLC) and Im et al. (2003) (IPS) panel unit root tests. Table 3 shows the results, which suggest the rejection of the unit root (null hypothesis) and stationarity for all variables at the same level except for real effective exchange rate (REER) and trade openness (TO). However, all variables were found to be stationary at their first differences in the IPS test and not the LLC test, where trade openness in oil countries and REER were found to contain unit roots in their first difference. Therefore, it is preferable to follow the IPS test, since it overcomes the limitations of the LLC test[1]. In particular, the current account balance, REER, TO and INV were not stationary at level, but they were stationary in first difference. Hence, a co-integration analysis is possible for the selected indicators.

Table 3. Panel unit root tests.

Ho: Panels Contain Unit Roots Ha: Panels Are Stationary	Level		First Difference	
	p-Value		*p*-Value	
Panel: full sample	LLC	IPS	LLC	IPS
Current account balance	0.0000	0.0011	0.0000	0.0000
Budget balance	0.0000	0.0001	0.0000	0.0000
Real effective exchange rate	0.0780	0.3281	0.0001	0.0000
Real GDP growth	0.0000	0.0000	0.0000	0.0000
Total investment	0.0042	0.0090	0.0042	0.0000
Trade openness	0.6288	0.4747	0.0000	0.0000
Panel: oil countries	LLC	IPS	LLC	IPS
Current account balance	0.0000	0.0006	0.0000	0.0000
Budget balance	0.0000	0.0007	0.0000	0.0000
Real effective exchange rate	0.1254	0.6960	0.0000	0.0000
Real GDP growth	0.0000	0.0000	0.0000	0.0000
Total investment	0.0003	0.0033	0.0000	0.0000
Trade openness	0.7619	0.3735	0.9730	0.0001
Panel: non-oil countries	LLC	IPS	LLC	IPS
Current account balance	0.2625	0.0550	0.0000	0.0000
Budget balance	0.0131	0.0092	0.0000	0.0000
Real effective exchange rate	0.2030	0.1266	0.3866	0.0000
Real GDP growth	0.0009	0.0000	0.0000	0.0000
Total investment	0.2170	0.2644	0.0000	0.0000
Trade openness	0.4307	0.5920	0.0154	0.0000

Note: the rejection of the null hypothesis (Ho) of a unit root at 10%, 5% and 1% levels of significance. Source: author's estimates.

Table 4 presents the results of the co-integration analysis implemented using the error–correction based panel cointegration test by Westerlund (2007). It tests for the co-integration relationship existence between two main variables: the budget balance and the current account balance in the full sample, oil and non-oil countries. The null hypothesis—(H0) of no co-integration—is rejected for the full sample according to the group mean and panel tests statistics presented in Table 4. This affirms a long-run steady-state relationship between the budget balance and current account balance, indicating a validity of TDH in the examined countries.

Table 4. Co-integration analysis.

Ho: No Cointegration	Panel: Full Sample	Panel: Oil Countries	Panel: Non-Oil Countries
	p-Value	*p*-Value	*p*-Value
Current account-Budget balance			
Westerlund (2007)			
Group Gt statistic (standard)	0.000	0.000	0.000
Group Ga statistic (robust)	0.005	0.003	0.000
Panel Pt statistic (standard)	0.000	0.000	0.000
Panel Pa statistic (robust)	0.000	0.000	0.000

Note: Gt and Ga are group mean statistics that test the null hypothesis (Ho) of no co-integration at 5% and 1% levels of significance for the whole panel against the alternative (Ha) of co-integration for some countries in the panel. Pt and Pa are the panel statistics that the null hypothesis (Ho) of no co-integration at 5% and 1% levels of significance against the alternative of co-integration for the panel as a whole. Source: author's findings.

3.2.3. PVAR and Granger Causality Analysis

Following the Panel Vector Autoregression (PVAR) approach by Abrigo and Love (2015), we test the dynamic effect of a budget balance shock and other variables on the current account balance. First, we selected the optimal lag order based on three main criteria: the Akaike information criteria (AIC), the Bayesian information criteria (BIC) and the Hannan–Quinn information criteria (HQIC) (Tables 5 and 6). PVAR model is conducted using GMM estimation of first order with same specification of instruments.

Table 5. Lag order selection criteria for oil-rich countries.

Lag	CD	J	J *p*-Value	BIC	AIC	QIC
1	0.9976262	89.75731	0.0766997	−254.9421	−54.24269	−135.7476
2	−0.0434123	43.06074	0.1947116	−129.289	−28.93926	−69.69174

Sample: 1994–2017 No. of obs = 120
No. of panels = 5
Ave. no. of T = 24.000

Table 6. Lag order selection criteria for non-oil countries.

Lag	CD	J	J *p*-Value	BIC	AIC	QIC
1	0.5777068	84.97333	0.1407282	−259.7261	−59.02667	−140.5316
2	0.593515	46.52938	0.1123666	−125.8203	−25.47062	−66.22309

Sample: 1994–2017 No. of obs = 120
No. of panels = 5
Ave. no. of T = 24.000

Second, after confirming the cointegration and lag selection of first order. We estimate the coefficients of this long-run relationship through GMM PVAR estimation. A positive significant relation between the two balances is found in oil-rich countries (Table 7). An increase in the budget balance by 1% results in an increase in the current account balance by 0.017%. Hence, the Keynesian proposition of the existence of a TDH is evident in oil-rich countries, where a budget surplus results in a current account surplus. The results support Eldemerdash et al. (2014), Morsy (2009) and Akanbi and Sbia (2018) for resource-rich economies and oil exporting countries. The reverse causality hypothesis—from current account balance to budget balance—is rejected as per the results presented in Table 8. This also reaffirms the unidirectional relation and supports the TDH hypothesis in oil-rich economies.

Table 7. GMM PVAR estimations—Oil countries.

Variables	Current Account	Budget Balance	ΔREER	GDP Growth	Total Investment	ΔTrade Openness
Lagged Current account	−0.0129291 (0.072)	−0.764252 (0.000)	0.1850592 (0.000)	0.9253072 (0.000)	0.3757229 (0.000)	−1.370283 (0.000)
Lagged Budget balance	0.0172951 (0.008)	0.8580624 (0.000)	−0.1587018 (0.000)	−1.134299 (0.000)	−0.2639757 (0.000)	1.411876 (0.000)
Lagged REERΔ	−0.0762447 (0.000)	−0.0835283 (0.000)	0.1517432 (0.000)	−0.130429 (0.000)	0.2774289 (0.000)	−0.271178 (0.000)
Lagged GDP growth	−0.0244887 (0.000)	−0.0116363 (0.011)	−0.0094626 (0.000)	−0.1450394 (0.000)	0.0143457 (0.000)	0.0443089 (0.000)
Lagged Total investment	−0.0529807 (0.000)	−0.0601517 (0.000)	0.0346498 (0.058)	−0.6200547 (0.000)	0.8403708 (0.000)	0.0558369 (0.205)
Lagged trade opennessΔ	−0.1869155 (0.000)	−0.4601908 (0.000)	0.3980776 (0.000)	−0.0510231 (0.595)	1.264939 (0.000)	−2.025962 (0.000)
Observations	130	130	130	130	130	130

Note: *p*-values in parentheses () and they indicate a significance levels at 5% and 1%. Δ Denotes that the variable is in first difference. Source: author's findings.

Table 8. Panel granger causality test—Oil countries.

Equation/Excluded	Chi2	df	*p* > Chi2
Current account			
Budget balance	7.035	1	0.008
REERΔ	47.094	1	0.000
GDP growth	707.110	1	0.000
Total investment	37.681	1	0.000
Trade opennessΔ	141.104	1	0.000
ALL	1326.821	5	0.000
Budget balance			
Current account	2095.158	1	0.000
REERΔ	82.910	1	0.000
GDP growth	6.387	1	0.011
Total investment	32.015	1	0.000
Trade opennessΔ	397.228	1	0.000
ALL	3620.204	5	0.000
Ho: Excluded variable does not Granger-cause Equation variable			
Ha: Excluded variable Granger-causes Equation variable			

Note: *p*-values reject the null hypothesis (Ho) indicate significance levels at 5% and 1% levels. Δ Denotes that the variable is in first difference. Source: author's findings.

On the contrary, results were different for non-oil countries. As shown in Table 9, a significant negative relation between the two balances was found. An increase in the budget surplus by 1% worsens the current account balance by 0.12%. This rejects the hypothesis of the existence of a TDH in those countries and rather supports the presence of Ricardian equivalence. This supports Akanbi and Sbia (2018) for a close group of MENA countries. While a bi-directional causality is proven (Table 10), the direction of causality doesn't matter as long as the relation is proven negative: A TDH is still rejected for non-oil countries.

Table 9. GMM PVAR estimations—non-oil countries.

Variables	Current AccountΔ	Budget Balance	REERΔ	GDP Growth	Total InvestmentΔ	Trade OpennessΔ
Lagged Current accountΔ	−0.4492705 (0.000)	−0.0759679 (0.000)	−0.0112542 (0.000)	−0.0694275 (0.000)	−0.0315228 (0.000)	−0.0055893 (0.028)
Lagged Budget balance	−0.1222366 (0.000)	0.6719996 (0.000)	0.0459064 (0.000)	0.0966541 (0.000)	−0.1038255 (0.000)	−0.0235697 (0.002)
Lagged REERΔ	0.136836 (0.003)	0.1475119 (0.198)	0.1966597 (0.000)	0.4415138 (0.000)	−0.4400424 (0.000)	−0.0595654 (0.009)
Lagged GDP growth	0.3784264 (0.000)	0.3527599 (0.000)	0.0264484 (0.083)	0.6512119 (0.000)	0.1763951 (0.000)	−0.0706059 (0.000)
Lagged Total investmentΔ	−1.301331 (0.000)	−1.248774 (0.000)	−0.342208 (0.000)	−0.376846 (0.022)	−0.1710501 (0.014)	−0.1046704 (0.000)
Lagged trade opennessΔ	0.6392724 (0.000)	0.7071824 (0.000)	0.8909835 (0.000)	−0.2462973 (0.040)	0.1311803 (0.034)	0.4609399 (0.000)
Observations	130	130	130	130	130	130

Note: *p*-values in parentheses () indicate a significance level at 5% and 1%. Δ Denotes that the variable is in first difference. Source: author's findings.

Table 10. Panel granger causality test- non-oil countries.

Equation/Excluded	Chi2	df	*p* > Chi2
Current accountΔ			
Budget balance	28.717	1	0.000
REERΔ	8.616	1	0.003
GDP growth	66.233	1	0.000
Total investmentΔ	75.287	1	0.000
Trade opennessΔ	33.699	1	0.000
ALL	188.665	5	0.000
Budget balance			
Current accountΔ	58.472	1	0.000
REERΔ	1.659	1	0.198
GDP growth	30.237	1	0.000
Total investmentΔ	97.756	1	0.000
Trade opennessΔ	24.088	1	0.000
ALL	143.399	5	0.000

Ho: Excluded variable does not Granger-cause Equation variable
Ha: Excluded variable Granger-causes Equation variable
Δ: Change in REER

Note: *p*-values reject the null hypothesis (Ho) and indicate significance levels at 5% and 1% levels. Source: author's findings.

Real effective exchange rate (REER) is an important channel between the budget balance and the current account balance[2]. Results show a negative relation between REER and the current account balance in oil-rich countries; that is, an appreciation in REER results in a current account deficit. This can be interpreted in light of the Mundell–Fleming framework where a real appreciation of a currency results in a loss of price competitiveness and a discouraged external demand (which reduces net exports). Thus, the current balance position is worsened. Conversely, a positive relation was found in non-oil countries; an appreciation in REER results in an improvement in the current account balance and vice versa. This can be interpreted in light of the lower trade elasticity in those counties, particularly given the fact that they are witnessing deficits most of the times and that exports and imports are less elastic to changes in exchange rates. Additionally, the fact that some of these countries adopt fixed exchange rates might also give an explanation to this low elasticity to changes in REER.

Opposite findings between oil and non-oil countries are also evident in other variables included in the model: namely trade openness and GDP. Trade openness was found to negatively impact current balance in oil-rich countries which is consistent with Eldemerdash et al. (2014) findings. Oil trade dependency is generally non-positively related to trade openness, since importing goods might harm the current account surplus produced from exporting oil. Oppositely, trade openness is significantly positively related to the improvement of current balances and the reduction of deficits in non-oil countries. Intuitively, more trade openness in countries with current account deficits—due to high dependence on imports—results in improvements in export positions, which improves the current account balance. Real GDP relation to current account balance is found to be negative in oil-rich countries and positive in non-oil countries.

3.2.4. Impulse Response Functions (IRF) Analysis

The purpose of the analysis of impulse response function (IRF) is to identify the performance of each variable and their dynamic relationship in the short-run and the long-run in response to shocks in other variables. The short-run is specified to be from period 0 to 5 while the long-run is specified to be from period 5 to 10. Figures 5 and 6 present the IRFs for oil-rich and non-oil countries, respectively. IRFs show no clear short-run response of the current account balance to a fiscal shock. In the long run, a positive fiscal shock has a positive impact on current account balance which, again, re-affirms the existence of a TDH in oil-rich countries. Oppositely, positive fiscal shocks have a negative effect on the current account balance in non-oil countries in the short-run that turns into a positive effect over the long run; that is to say, TDH is rejected in non-oil counties in the short run only.

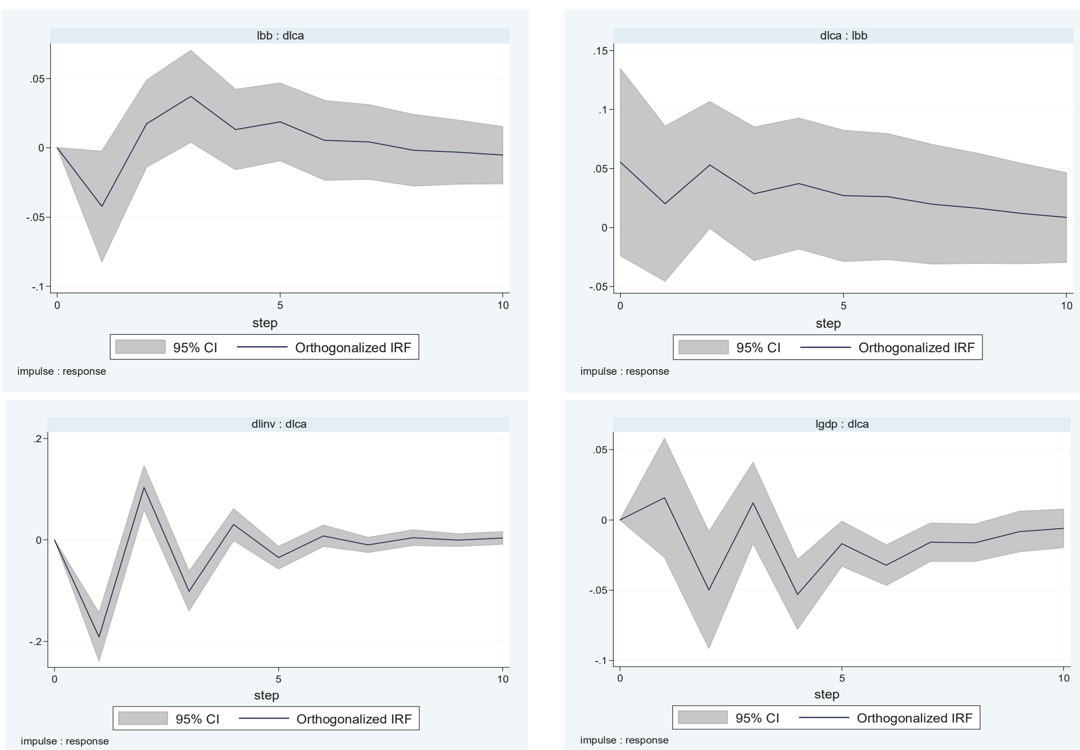

Figure 6. *Cont.*

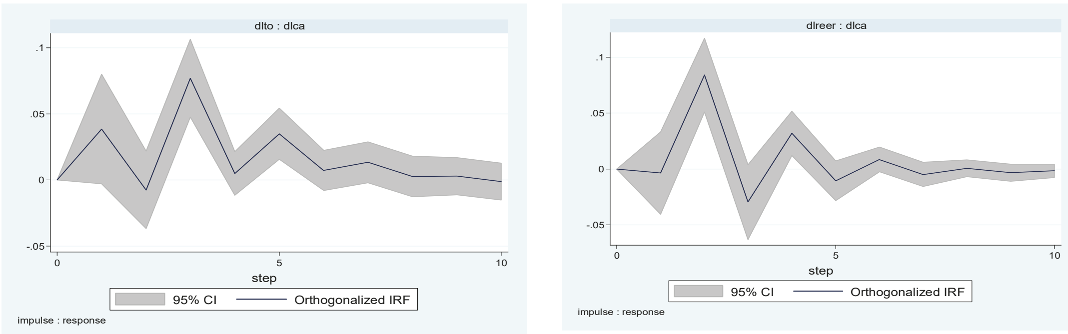

Figure 6. Impulse response function (IRF) for non-oil countries.

4. Conclusions and Policy Recommendations

The paper examines the relationship between the fiscal and external balances in the MENA region in an attempt to answer the question of whether geopolitics and oil-price dynamics contribute to the changing the relation between the fiscal variables and the current account variables in the context of the twin deficits hypothesis (TDH). Descriptive analysis, as well as PVAR GMM estimation, indicate the existence of TDH in oil-rich countries only. Oppositely, no sufficient empirical evidence on its existence in non-oil countries was found. Rather, our findings support a Ricardian equivalence hypothesis in those countries. We argue that oil dependence poses a strong influence on fiscal performance in MENA oil-rich countries and, consequently, on exports and trade balance. This makes those countries more fiscally and externally vulnerable to geopolitical tensions and oil price dynamics. The argument that adopting fixed exchange rate regimes in oil-rich countries magnifies such vulnerabilities is also supported by our empirical results.

Oppositely, for non-oil countries, fiscal and external balances problems mainly occurred as a result of structural problems. In in the examined non-oil countries, we have observed the high reliance on tourism revenue remittances as the main sources of foreign currency receipts. In addition, many of the examined countries suffer from poor tax revenues and enlarged current spending bills (inflated public sector, large subsidies system, high interest payments, etc.), altogether limiting fiscal space and increasing vulnerabilities to both domestic and external shocks. It is also worth noting that most of the reviewed countries have a large imports sector, which makes the countries' external accounts also weak and more vulnerable.

A number of policy implications can be drawn from the above research exercise:

- Primarily, reforming fiscal performance in oil-rich countries is not of less importance than non-oil ones. Oil-rich countries need to reform their fiscal performance in the sense that they need to decrease the reliance on oil revenues and develop the non-oil sector. Those countries are also urged to revise their currency regimes towards more flexible regimes in order to decrease the vulnerability to external shocks.
- Secondly, regarding non-oil countries, fiscal or current account targeting might not be the proper solution under the Ricardian equivalence hypothesis, since most of the examined countries suffer from persistent structural deficits. Those countries need to adopt fiscal consolidation programs that aim at reforming their spending structures on one side as well as improving sources of revenues; particularly tax administration on the other side.
- Thirdly, Non-oil countries need to also adopt rather flexible exchange rate regimes in order to decrease the vulnerability of the external sector to domestic, regional and global shocks.
- Finally, export-led growth strategies and inclusive growth policies would also contribute to improving external accounts in the examined economies.

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Notes

1 More on the IPU tests as opposed to the LLC tests can be found in Gengenbach et al. (2009).

2 An increase in REER is a real appreciation and a decreasing index of REER is a real depreciation of the currency.

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Short-Term Event-Driven Analysis of the South-East Asia Financial Crisis: A Stock Market Approach

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Abstract: A systematic short-term event review of the major events in the South-East Asia Financial crisis is presented in this article. This analysis adds to the existing literature by focusing on the equity market, rather than on the foreign exchange market where there is already abundant literature, as well as going to a granular level with the hope that the analysis of the short-term market reactions can help policy-maker make appropriate decisions understanding the likely implications on the stock market. Short-term movements in the equity market might have very substantial economic impacts on investors and on the broad economy. The existing literature tends to focus on longer time horizons but from an equity investor point of view short-term fluctuations might be equally important or even more. When analyzing longer time horizons these short-term fluctuations, which might cause investors to fully unwind their positions or even bankruptcies, might be average out, underestimating the potential impact on the investor. Given these practical considerations it seems important to carry out a short-term event driven analysis of this crisis.

Keywords: financial-crisis; South-East Asia; event driven

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1. Introduction

The South-East Asia financial crisis of the late twentieth century was an unexpected (Krugman 1999) development that saw a rapid deterioration of the economies (Suryahadi et al. 2012) and financial markets (Choudhry et al. 2007; Click and Plummer 2005; Khan et al. 2009) of several South-East Asian countries. Several of the countries directly impacted by the crisis had experienced significant economic growth in the years previous to the crisis (Huang and Xu 1999). There were several major events during the crisis, such as Thailand floating the currency as well as political changes such as the high profile replacement in Malaysia of the finance minister, creating a very complex economic and financial situation. External factors, such as the IMF intervention, have been also frequently cited as detrimental (Bello 1999) further adding complexity to the crisis with some authors, such as Pilbeam (2001), suggesting that some of the programs introduced by the IMF were too harsh. In fact, Miller (1998) considers that it is more precise describing the situation as multiple crisis occurring simultaneously rather than a single crisis.

Akyuz (1998) mentioned the substantial differences in the economies of the countries involved in the crisis. Some of the countries/regions more heavily impacted by this crisis were Thailand, where the crisis arguably started, Malaysia, Indonesia, South Korea, and the Philippines.Some authors, such as Dickinson and Mullineux (2001), have mentioned that one major factor behind the crisis was the ineffective financial regulation in some of the countries impacted. Singapore and Hong Kong were also involved in the financial crisis but they were significantly less impacted (Jin 2000), arguably due to a combination of stronger (pre-crisis) financial oversight and regulations as well as relatively high foreign exchange reserves. To put it into context, the Singaporean economy contracted in 1998 only 2.2%. Of the countries directly involved in the South-East Asia financial crisis, only the Philippines experienced a smaller contraction in 1998. Indonesia for instance had a GDP contraction in 1998 of 13.1%. Authors such as Tee (2003) mentioned that the credibility of the Singaporean dollar exchange rate and the sound economic situation of Singapore before the South-East Asia financial crisis were among the major factors protecting the currency during this period; nevertheless, Singapore was clearly also impacted. The capital markets as well as the currencies of most of the above mentioned countries and jurisdictions were impacted to various degrees (Goldstein 1998). Notably, not all the Asian currency pegs were broken during the crisis with for instance Hong Kong managing to successfully defend the Hong Kong dollar from multiple speculative assaults. One factor facilitating maintaining the peg was the large reserves of foreign capital held by Hong Kong, second only in the region of those of Mainland China (Chirathivat 2007). Hong Kong strongly defended the currency peg with the Monetary Authority of Hong Kong, the de facto central bank of Hong Kong, using its reserves to support the Hong Kong dollar. For instance, it was reported that the HKMA spent in two hours on 24 July 1997 one billion U.S. dollars supporting the Hong Kong dollar (Kearney and Hutson 1999). Some authors, such as Bennett (1994), have mentioned the importance of the different types of peg. Bennett (1994) compares the case of Hong Kong with a hard peg and Singapore with adjustable peg.

While Hong Kong overcame the South-East Asia financial crisis better than most of its regional neighbours and was able to maintain the peg with the U.S dollar, it was also clearly affected by the crisis. According to data from the IMF, the Hong Kong economy managed to grow in 1997, with GDP up 5.1%, but contracting in 1998 by approximately 5.5%. Economic growth remained positive in the following years. The performance of the Hong Kong economy during this period considerably lagged that of Mainland China. Remarkably, Mainland China did not have during this period a single year of negative growth with GDP increasing 9.3% and 7.8% in 1997 and 1998, respectively. GDP growth in the post-crisis period in Hong Kong remained positive but volatile with oscillations such as a GDP increase of 10.0% in 2000 followed by a GDP increase of only 0.6% in 2001. The stock market in Hong Kong was also impacted by the crisis with the Hang Seng Index down approximately 46% from the peak in 7 August 1997 of 16,673 to the bottom of 28 October 1997 of 9059.

The 1997 South-East Asia financial crisis brought to an abrupt stop (Miller (1998)) the remarkable rates of economic growth experienced by several of the countries in the region. Some authors, such as Corsetti et al. (1999), suggest that the South-East Asia financial crisis of 1997–1998 was the culmination of a series of long standing pre-existing structural imbalances rather than a single major event precipitating the crisis but this remains an area of debate. The degree of development and sizes of these economies involved were remarkably different. As previously mentioned, one of the most visible and first events during this financial crisis was the collapse of the Thai currency (baht) adding pressure on Thai companies that have borrowed on U.S. dollars. This is in fact the start of the crisis according to authors such as Leightner (2007). The situation in Thailand rapidly spread to other countries (Jomo 1998).

Most of the existing literature in the South-East Asia financial crisis focuses on the impact on the real economy as well as in the fluctuations in the foreign exchange market (Woo et al. 2000). This is perhaps due to some very high profile developments in the foreign exchange market such as the well-known bet of George Soros against the baht. There are also some interesting research, such as Beaverstock and Doel (2001), mentioning the role played by the baking sector, of both domestic institutions as well as of the international investment banks.

There is however relatively less literature covering the impact on the stock market, particularly from a short-term event driven angle. Short-term fluctuations in the equity market might have a very substantial impact on investors, particularly if their investments are leveraged or it they are forced to unwind their trades due to margin calls or risk management considerations. Unwinding these positions, during unfavorable market movements, might negate the benefits of a future recovery in the market. There is ample literature suggesting that there are volatility clusters in several equity markets (Cont 2007; Lux and Marchesi 2000) and such clusters might potentially be related to a major event.

An example of such an event could be Thailand letting its currency to free float during the South-East Asia financial crisis on 2 July 1997. Until that moment, most South-East Asian countries have defended their currencies, many of them pegged to the U.S. dollar. A related factor frequently mentioned in the existing literature (Radelet and Sachs 1998) is the spread of financial panic. In this paper, we carry out a short-term event driven Granger causality analysis using some important events cited in the existing literature. Granger causality tests are a frequently used technique to analyze dependencies between financial variables (Ibrahim 2000). The analysis focuses on the impact on the equity markets rather than the impact on the foreign exchange market.

One of the assumptions underlying this paper is that some events, such as, for instance, the end of a currency peg, can trigger significant movements in the local equity market. Furthermore, the impact on those events can also spread to other markets, particularly regional, also impacting their performance. It seems also reasonable to assume that in principle this market fluctuations can be short lived, averaging out over long periods of time, but having substantial impact in the short term. In order to analyze these events, it is necessary to have the appropriate mathematical and statistical tools. Note that the focus on this paper is on trying to determine the changes in interdepenedencies of stock markets rather that on trying to forecast the stock prices themsleves. In recent years, there has been a focus on using machine learning techniques generating interesting results, such as, for instance, neural networks (Cervello and Guijarro 2020; Garcia et al. 2018). However, the analysis in this paper focus on changes in the dynamics of the market with actual forecasting outside of the scope. An underlying assumption in this analysis is that the Granger causality test can detect some causality relationships. This is a common assumption in multiple articles such as Hoffmann et al. (2005); Akinboade and Braimoh (2010), and Lopez and Weber (2017). It is not assumed that the Granger causality test fully accurately reflects underlying causality relationships, but it is rather used as a quantitative indication of their existence. In other words, the Granger causality test reflects Granger causality rather than true underlying causality. Nevertheless, it is important to have a quantitative test that can be applied objectively to the data to try to minimize as much as possible the potential for biases in the analysis.

2. Some Major Events during the South-East Asia Financial Crisis

It is a challenging task to identify the major events during any financial crisis and the South-East Asia financial crisis is no exception and even more complex to determine the factors that might impact the equity market. For instance, besides objective financial conditions there is some existing research on the impact of investors sentiment (Guijarro et al. 2019) on the equity market. This could be a particularly important factor to be taken into consideration during financial crisis. It is also acknowledged that there is some degree of subjectivity and that there are some other events that could potentially be considered. Nevertheless, it is necessary when attempting to carry out an event driven analysis, to identify a list of such events that are significant enough to have had a large impact on the stock market. In this case of the South-East Asia financial crisis, seven events (Table 1) were identified as substantial enough to potentially having the capacity to impact the stock market. These events range from 2 July 1997 (Jansen 2001) that saw the end of the Thai baht peg (event 1) to 3 September 1998 with the replacement of the finance minister in Malaysia (event 7). Some authors such as Jansen (2001) consider that the start of the South-East Asia financial crisis was July 1997, coinciding with the end of the Thai baht peg. Krongkaew (1999), more explicitly, mentions that the start of the economic crisis occurs in Thailand with the flotation of its currency. Thus, this event should be one of those analyzed.

Table 1. List of some major events during the South-East Asia financial crisis.

Event	Date	Description
1	2 July 1997	End of the Thai baht peg
2	14 August 1997	Indonesia let the currency to free float
3	14 October 1997	Restructuring package announced by Thailand
4	12 January 1998	Collapse of Peregrine investment
5	31 March 1998	Thai guideline of definition of non-performing loans
6	11 May 1998	Joseph Estrada wins general elections in the Philippines
7	3 September 1998	Finance minister of Malaysia replaced

Pressure had been building on the Thai economy since early 1997 and was becoming evident with the default of Somprasong Land (Lauridsen 1998; Wong 2001), a property developer, adding concerns about the health of property developers. However, this event by itself did not appear to have caused an impact on the broad financial market or economy. Another factor to take into account was the increasing pressure from hedge funds Robins (2000) on the baht. Perhaps some of the best known hedge funds to bet against the baht during this period are the Quantum Fund and Tiger Fund with a reportedly one and three billion U.S. dollars short positions on the currency, respectively. Note that the actual impact that the hedge funds had on the South-East Asia financial crisis remains a disputed topic with authors such as Brown et al. (2000) not founding empirical evidence that hedge funds caused the financial crisis in Thailand. Regardless of the actual impact of hedge funds, the situation in the currency front eventually became unsustainable and Thailand had to float its currency. After the flotation of the Thai baht there was an almost immediate overnight depreciation compared to the U.S. dollar (Punyaratabandhu 1998) putting substantial pressure on Thai companies that had borrowed in U.S. dollar terms. The deterioration in returns combined with large amounts of borrowings in foreign currency plus a significant devaluation of the baht proved to be a combination that hurt a large amount of Thai companies that were unable to repay their borrowings. Jansen (2001) and several other scholars have mentioned that financial institutions as well as companies got used to have a stable currency pegged to the U.S. dollar creating a false sense of security and causing poor risk management. According to these authors, the possibility of a sudden change in the exchange rate of the baht was regarded as a rather remote possibility and this perception was based on many years of stable foreign exchange values and growing economy. While there were financial tools for hedging currency exposure the borrowing from Thai domestic companies was predominantly not hedged (Takayasu 1998) and thus companies had to absorb loan repayments denominated in U.S. dollar while the local currency was rapidly depreciating.

Another event considered (event 2) was Indonesia letting its currency to free float in 14 August 1997 (Pratomo and Warokka 2013). This was arguably unavoidable after Thailand ended its peg a few weeks earlier with the Indonesian currency reserves coming under increasing pressure during those weeks. In the initial stages of the financial crisis Indonesia showed some signs of resilience. This situation quickly changed with the local currency slumping and a run on the banking sector putting the national finances under considerable stress. One of the first clear signs of stress in Indonesian economy appeared in the currency market with the Indonesian rupiah slumping against the U.S. dollar from July 1997 to January 1998. Indonesia had started a process of liberalizing the exchange rate system (James 2005) in the previous decades and by 1997 the Indonesia rupiah traded within a relatively narrow band relatively to the U.S. dollar. Given the increasing pressure on the currency and the cost of defending it, Indonesia decided on 14 August 1997 to float the currency. The regime shift added significant amount of volatility to the exchange rate and increased economic pressure. Some authors, such as, for instance, Pratomo and Warokka (2013), have argued that the Indonesian rupiah was not a stable currency even before the South-East Asia financial crisis and that if more efforts were have done to stabilize it in the years before the crisis the rupiah should have hold substantially better during the crisis period.

After a turbulent summer of 1997, several of the countries engulfed in the crisis developed economic plans to tackle the crisis, such as for instance the restructuring package introduced by the Thai government in 14 October 1997 (event 3). This restructuring initiative received the praise of the IMF with IMF managing director, Mr. Michel Camdemssus, stating "The Thai government has made a significant announcement today about its detailed strategy to restructure Thailand's troubled financial sector." An important development of this initiative was the creation in Thailand of the Financial Sector Restructuring Authority commonly known as FRA (Hawkins 1997). FRA was one of the main agencies in charge of assessing the economic situation and handling troubled financial assets and had a wide range of powers including the ability to request troubled financial companies to recapitalize or to arrange acquisitions by third parties.

An event that attracted substantial attention during the South-East Asia financial crisis was the collapse or Peregrine Investments in early 1998 (event 4). Peregrine Investments went into liquidation in January 1998 in Hong Kong. At the core of the collapse of Peregrine Investments was a 269 million U.S. dollar loan to a taxi company in Indonesia called PT Steady Safe. Several attempts to restructure the loan were unsuccessful with the company going into liquidation relatively quickly after the start of the South-East Asia financial crisis. Note that Peregrine Investments was a very well-regarded institution with diversified operations across Asia and to a lesser degree in Europe and the US. At the time of its collapse it was one of the largest independent investment bank in Asia. A few months later, in 1998, there was a subtle but important development with Thailand modifying the definition of non-performing bank loans (event 5). The objective of this measure was to make the definition of non-performing bank loans in Thailand in line with the international accepted guidelines (Takayasu 1998). While a positive development, this reclassification arguably added in the short term more pressure on the market as international standards at the time were more stringent.

Another event considered was the successful presidential campaign of Mr. Joseph Estrada in the Philippines (Claudio 2014; Ringuet and Estrada 2003), representing the political party PMP, becoming president after winning the elections in 11 May 1998 (event 6). Estrada won the election with a populist message (Hedman 2001), promising alleviating poverty. The Philippines was one of the very few Asian countries, at the time of the South-East Asia financial crisis to have a fund deposit insurance scheme (Kochhar et al. 1998), likely helping alleviating runs in the Philippines banks. Additionally the banking sector in the Philippines was less exposed to the real estate sector (Table 2) that most of its regional peers. This is not to say that the banking system of the Philippines had no significant exposure to the real estate sector. According to Bello (1999), the commercial bank loan exposure of the Philippines to the real estate sector was approximately 20% in the period just before the financial crisis, while the real estate exposure in Indonesia during the same period was approximately 25% (Bello 1999). Several authors, such as Krugman (1999), have mentioned that a major issue was that a large amount of the capital borrowed overseas was directed towards investment in real estates. In many occasions, foreign capital was cheaper than domestic one and companies borrowed in foreign currency increasing their foreign exchange risk.

Table 2. Banking system exposure to the real estate sector. Source: Bank of International Settlements.

Country	Country Exposure (%)
Indonesia	30
Malaysia	40
Philippines	20
Singapore	40
South Korea	25
Thailand	40

A lesser exposure of the banking sector to property developers was one of the factors allowing the Philippines to be relatively less impacted than its peers by the crisis with for instance, according to figures from the World Bank, having the smaller GDP correction in 1998 (Table 3).

Table 3. GDP (1998). Source: World Bank.

Country	Country Exposure (%)
Indonesia	−13.1
Malaysia	−7.4
Philippines	−0.6
Singapore	−2.2
South Korea	−5.5
Thailand	−7.6

This is not to say that the Philippines were untouched by the financial crisis. For instance, the Philippine peso experiencing a depreciation against the U.S. dollar of approximately 37% from June 1997 to September 1998, which is in line with most of the Asian neighbors such as Thailand, Malaysia, and South Korea. The last event considered was the abrupt replacement of the finance minister in Malaysia in 3 September 1998. Malaysia faced significant internal political turmoil during this period with public disagreement between the members of the Malaysian government regarding how to react to the crisis with on one hand the Prime Minister Mahathir Mohamad (Kelly 2001), against accepting the bailout offer from the IMF, and on the other hand, the finance minister that supported this idea and was an advocate of free markets. The finance minister was replaced (Sundaran 2006) and Malaysia continued its strategy of not requesting a bailout from the IMF (Sausmarez 2004).

Prime Mister Mahathir mentioned that the IMF would have requested too stringent economic reforms and that IMF will focus only on loan repayments rather than on economic growth which was according to Prime Minister Mahathir not an acceptable approach for the country. Malaysia initial response to the crisis has been described by some scholars as a “state of denial” (Ariff and Abubakar 1999) with the government downplaying the seriousness of the situation. One of the first clear indications of the severity of the financial crisis was the depreciation of the Malay ringgit. The central bank of Malaysia (Bank Negara Malaysia) tried to support the currency purchasing at the beginning of July 1997 in excess of one billion U.S. dollar. It has been highlighted by some scholars that despite refusing the intervention by the IMF the Malay government immediate response was roughly in line with the IMF suggestions, by substantially decreasing government spending and delaying major projects such as railways and the emblematic Bakun dam (Ariff and Abubakar 1999) and banning short term repatriation of capital (less than 12 months).

Nevertheless, the severity of the economic situation became self-evident rather quickly and the Malay government reacted by establishing, in the beginning on 1998, the National Economic Action Council, which could be described as a think-tank helping the government drafting policies to overcome the financial crisis. Eventually the government took two major decisions: (1) strict capital control and (2) peg of the currency to the U.S. dollar at a 3.8 rate. This meant that the offshore ringgit was no longer convertible, basically closing the offshore foreign exchange market and forcing some repatriations of ringgit into Malaysia. Furthermore, Malaysia went a step further by declaring the Malay ringgit illegal tender outside Malaysia and by freezing non-resident bank accounts holding deposits denominated in Malay ringgit. Despite all these measures, the depreciation of the Malaysian ringgit compared to the U.S. dollar during the South-East Asia financial crisis was in line with most of its Asian neighbors, such as Thailand, Philippines, and South Korea.

3. Methodology

A systematic approach was followed in this paper including in the analysis not only South-East Asian countries but also emerging and non-emerging countries in order to make the comparisons more reliable as well as in order to determine base line pre-existing relationships. An underlying assumption is that financial crisis can cause contagion among the equity markets of different countries (Kernourgios et al. 2011). A short-term event driven Granger causality test was performed among all the 23 countries/regions analysed (Table 4). Granger causality tests have been applied to the stock market in several paper such as Hiemstra and Jones (1994). A set of events, previously identified in Table 1, were used as critical dates representing significant developments such as for instance Thailand floating the baht. This differs from most of the analysis in the existing literature that tend to segment the analysis into the pre, post, and crisis periods (Jang and Sul 2002) rather than going to a more granular level during the actual financial crisis. For each event a time period, including ten days before and ten days after the events, was analyzed. This period of time was chosen to avoid overlap between the different events which can make the interpretation of the results more difficult. Following the standard notation the variables can be described as (Equation (1))

$$y_{i,t} = \alpha_{0,i} + \alpha_{1,i}y_{i,t-1} + \alpha_{2,i}y_{i,t-2} + \ldots + \alpha_{j,i}y_{i,t-j} + \beta_{1,i}x_{i,t-1} + \beta_{2,i}x_{i,t-2} + \ldots + \beta_{j,i}x_{i,t-j} \quad (1)$$

The inputs for the Granger causality test were the daily returns on the indexes of all countries/regions analyzed for the previously mentioned periods (Equation (2)).

$$R_{t+1} = \frac{P_{t+1}}{P_t} - 1 \quad (2)$$

The Granger causality test was carried out using 2, 3, and 4 days lag. The data for all the stock equity indexes were obtained from Bloomberg.

Table 4. GDP (1998). Indexes included in the Granger causality test.

Country/Region	Stock Index	Country/Region	Stock Index
Argentina	Argentine MERVAL	Netherlands	Netherlands AEX
Australia	S&P ASX 200 Australia	New Zealand	NSZE
Austria	ATX Austria	Pakistan	Pakistan KSE
Belgium	Belgium BEL 20	Peru	S&P BVL Peru
Canada	S&P TSX 60 Canada	Philippines	Philippine PCOMP
France	France CAC 40	Portugal	Portugal PSI 20
Germany	Germany DAX	South Africa	FTSE JSE
Hong Kong	Hang Seng Index	South Korea	Kospi
Indonesia	Indonesia Jakarta Composite	Spain	IBEX 35
Japan	Nikkei 225	Thailand	Thai SET
Malaysia	FTSE Malay KLCI	United States	Dow Jones Industrial
Mexico	S&P BMC Mexico		

This type of analysis aims to analyze events in isolation. It is acknowledged that events do not occur in isolation and that there are other moving parts. Nevertheless, the events described in Table 1 are likely significant enough to have, by themselves, an impact on the stock market. A total of 23 countries/jurisdictions were included in the analysis. The Granger causality tests were carried out including all the pairs of stock indexes analyzed. The Singaporean stock market was not included in the analysis. This is due to data availability during the time period analyzed. Given the number of data points, using more than a four-day lag does not appear to be advisable. It is also acknowledged that a Granger causality tests does not necessarily infer real causality relationships between to events, but it is nevertheless an empirically objective test that can add some support to the existence of real underlying causality relationships between the variables analyzed. Given that the Granger causality test of 23 countries are analyzed in pairs, for seven different major events an including three different lag terms the number of tests is clearly rather large.

Another important factor that needs to be taken into account is that there could be structural, pre-existing relationships between the countries/regions analyzed and that these pre-existing relationships need to be taken into account during the analysis. For instance, it would be likely that the stock market of a country would have an impact on the performance of the stock market in its region. In order to account for those relationships a base line Granger causality relationships was established using the index returns before the crisis. More specifically, the returns of the indexes were calculated for the 1996 calendar year and the related Granger causality tests calculated. Existing causality relationship before the crisis period were excluded from the list of Granger causalities relationships for each of the seven events analyzed. In this way it was obtained a list of filtered Granger causality results.

The adjusted volatility for each of the seven periods analyzed was also estimated. The first step consisted in calculating the daily standard deviations (Schwert 1990) for all the seven periods analyzed (σ_p). This volatility by itself is difficult to interpret so it was scaled by dividing it by the average volatility of a reference period (σ_{Ref}) before the financial crisis (1996). The resulting number ($\sigma_{Adjusted}$) is dimensionless as it represents the ratio between two standard deviations (Equation (3)).

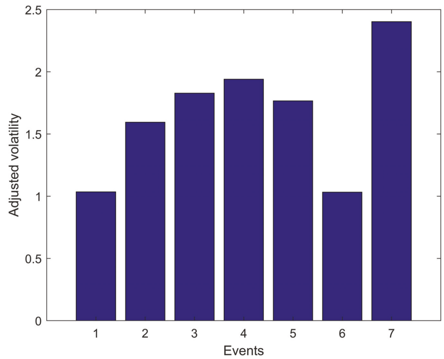
$$\sigma_{Adjusted} = \frac{\sigma_p}{\sigma_{Ref}} \tag{3}$$

The larger the number is the more volatile the market was, compared to the base line level, during the event analyzed. A formal F-test comparing the volatility for each indexes in each event with the base line volatility was also carried out. The null hypothesis is that the volatility of the two distributions (base line and during the event) are the same.

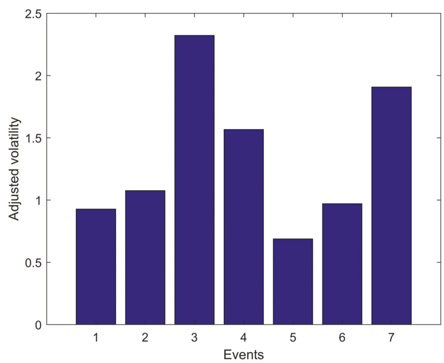
4. Results

The results suggest that there are three distinct phases, from a stock market volatility point of view. Initially, the crisis was mostly regional in nature (event 1), mostly impacting emerging markets in South-East Asia. Volatility started to spread to other markets, such as for instance Japan (Figure 1a) and even developed markets as different as Australia (Figure 1b). This process reached its peak approximately at event 4. After that initial phase of increasing volatility (from event 1 to 4), volatility started to gradually return more normal historical levels. Volatility then experienced another spike during event 7. The results illustrated graphically with the adjusted volatility values were formally tested using F-tests. As previously mentioned the volatility for each event and each index was compared to the volatility during the base line period (1996). The result of the graphical approach and the formal statistical test are consistent with all the markets analyzed having statistically higher volatility during events 3, 4 and 7 compared to their base line levels.

In order to estimate a base line the pre-existing (1996), Granger relationships were analyzed. During this period, the stock market of the countries in the region did not appear, according to the Granger analysis, to be a major driver of other markets. For example, Indonesia was only driver (Granger causality) of the Hong Kong and Portugal markets (using 2 day lag) and the Philippines was only a driver of the Thai market. Hong Kong was a driver of Argentina, Indonesia, and the Netherlands, and Japan of Austria, Indonesia, and the Netherlands. Some of these Granger relationships might be the result of spurious data relationships not based on strong underlying economic reasons however some of those relationships seem consistent with expectations, such as for instance, Philippines and Thailand. Similar results were obtained when the analysis was carried out with 2 and 3 days lag. Overall, there were less than expected pre-existing relationship (Granger causality) among countries in the South-East Asia region. In the following sections the results for each event are presented.



(**a**) Adjusted volatility for Japan during all the considered events

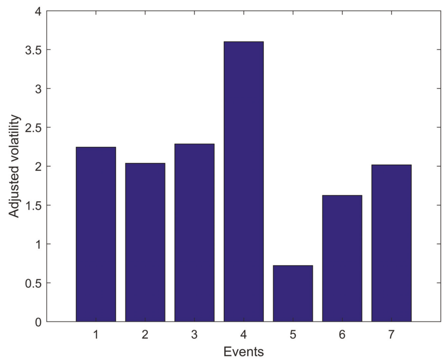


(**b**) Adjusted volatility for Australia during all the considered events

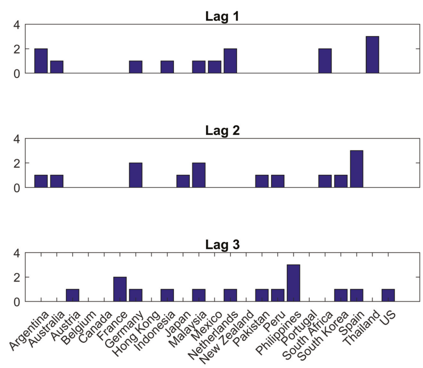
Figure 1. Examples of adjusted volatility.

4.1. Event 1—2 July 1997

Thailand letting the Thai baht to freely float is arguably one of the most important event during the South-East Asia financial crisis. The results from the F-tests (Appendix A Table A17) comparing the volatility of the stock markets suggest that at this stage the South-East Asia financial crisis was mostly a regional event. The volatility during this event was statistically higher than in the baseline period (1996) only in 6 out of the 24 countries analyzed, most of these countries where the volatility was significantly higher were countries directly related to the crisis such as Thailand and the Philippines. As illustrated in Figure 2a, Thailand, since event 1, started having high adjusted volatility levels of almost twice its base line levels. This is a reasonable result considering that letting the Thai baht to float, after a long period of stable exchange rates, likely substantially impacted the performance of the Thai stock exchange. In Figure 2b it is shown the results from the Granger causality tests (adjusted for baseline effects) using three different time lags (1, 2, and 3 days). The number of statistically significant Granger causality relationships was relatively low. Using 1 and 2 days lag there were only 14 statistically significant Granger causality relationships while 15 relationships were found when using 3 days lag. Interestingly during this first event, the Thai stock market, according to the Granger causality test, did not substantially impact other markets after adjusting for base line relationships. Perhaps this is related to investors, at that initial stage, considering that it was mostly a local issue. The stock market of Malaysia seems to have impacted, during this period, the stock market of Thailand (1-day lag) and Japan (2- and 3-day lag).



(**a**) Adjusted volatility for Thailand during all the considered events.

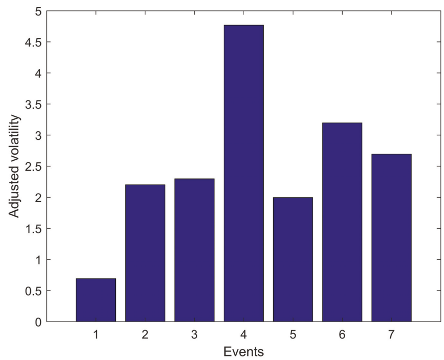


(**b**) Results of the Granger causality tests after filtering for event 1

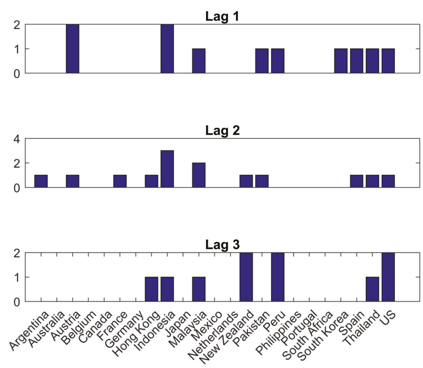
Figure 2. Adjusted volatility for Thailand and Granger analysis of event 1.

4.2. Event 2—14 August 1997

After several attempts to defend its currency on 14 August 1997, Indonesia decided to float its currency. The Indonesian Central Bank tried robustly to defend its currency but pressure was gradually increasing and foreign reserves were not large enough. Indonesia was initially not too severely affected. In fact, at the beginning of the financial crisis it was considered a success story. However, that rapidly changed with volatility doubling compared to its baseline level during the event 2 period. In the Indonesian case, volatility remained elevated for prolonged periods of time. The stock market experienced the same phases as previously mentioned with an initial phase of sustained volatility increases, peaking in event 4, followed by a phase of lower volatility, around event 6. The main difference in the Indonesian case compared to some other markets is that this phase of lower volatility was shorter with a volatility spike during event 6. Volatility remained high during event 7. The number of Granger causality relationships remained low during this period at 11, 14 and 10 for lags of 1, 2 and 3 days, respectively (Figure 3).



(**a**) Adjusted volatility for Indonesia during all the considered events



(**b**) Results of the Granger causality tests after filtering for event 2

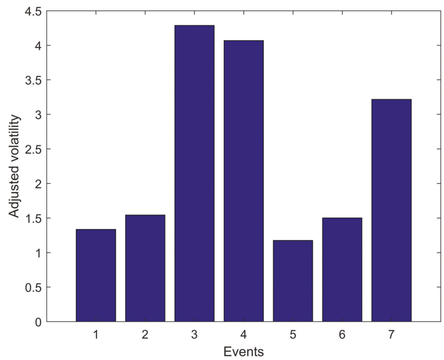
Figure 3. Adjusted volatility for Indonesia and Granger analysis of event 2.

4.3. Event 3—14 October 1997

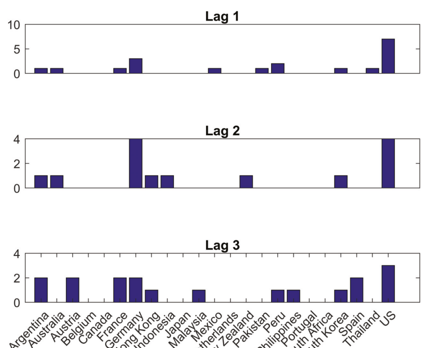
In 14 October 1997, Thailand announced a restructuring package in another of the major events during the South-East Asia financial crisis. In this event volatility remained high compared to historical levels. In fact, from event 1 to 3 volatility was roughly twice the base line levels volatility of 1996. The number of statistically significant Granger causality relationships was one of the lowest during this period with only 10, 10, and 17 relationships identified when using 1-, 2-, and 3-day lag, respectively. A bidirectional relationship between the stock markets of South Korea and Indonesia was identified when using the Granger test (3-day lag).

4.4. Event 4—12 January 1998

Another important event during the financial crisis was the collapse of Peregrine investment on 12 January 1998. The investment company was based in Hong Kong but it failed due to losses for a transaction in Indonesia. As it can be seen in Figure 4a volatility in the Hong Kong stock market was significantly higher than the base line levels during events 3 and 4. Note that Hong Kong did manage to successfully defend its peg to the U.S. dollar but clearly its stock market was substantially impacted by the crisis. The same phases as in other markets can be identified in Hong Kong with a primary spike in volatility around event 3 and 4 and a secondary spike around event 7. As shown in Figure 4b, the Indonesian market experienced a drastic increase in volatility in event 4 passing from approximately twice its baseline level in event three to more than four times during event 4. The number of Granger causality relationships identified as statistically significant (adjusted for base line level) remained relatively moderate during the event 4 period with 19, 14 and 18 relationships using 1-, 2-, and 3-day lags.



(**a**) Adjusted volatility for Hong Kong during all the considered events



(**b**) Results of the Granger causality tests after filtering for event 4

Figure 4. Adjusted volatility for Hong Kong and Granger analysis of event 4.

4.5. Event 5—31 March 1998

On 31 March 1998, another major development in the South-East Asia financial crisis happened with Thailand releasing new guidelines for the definition of nonperforming loans. Event 5 coincides with one of the lowest adjusted volatility periods for the markets analyzed. By event 5 there started to be clear, statistically significant signs of contagion among different stock markets with Granger causality relationships, adjusted by base line effects, increasing regardless of the lag used. The Granger causality relationship found using 1, 2 and 3 days lags were 34, 47, and 30, respectively (Figure 5).

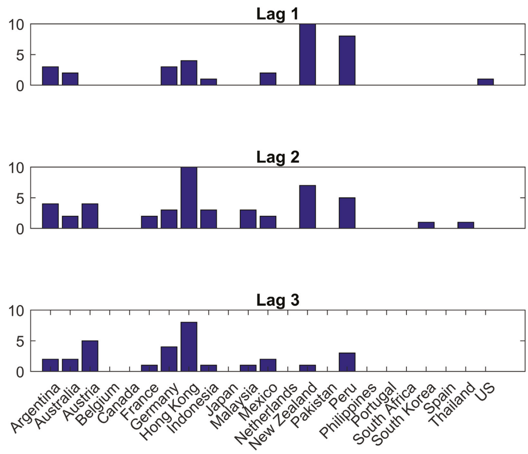


Figure 5. Results of the Granger causality tests after filtering for event 5.

4.6. Event 6—11 May 1998

On 11 May 1998 Joseph Estrada won the general elections in the Philippines in another major development during the South-East Asia financial crisis. During this event volatility started to increase again compared to the previous events for most of the markets analyzed. The Granger causality tests identified 13 causality relationships among the countries, using a one-day lag period. When using 2 and 3 days lag there were 17 and 25 Granger causality relationships respectively (Figure 6). A bidirectional relationships was found between the US and Canadian markets (3-day lag).

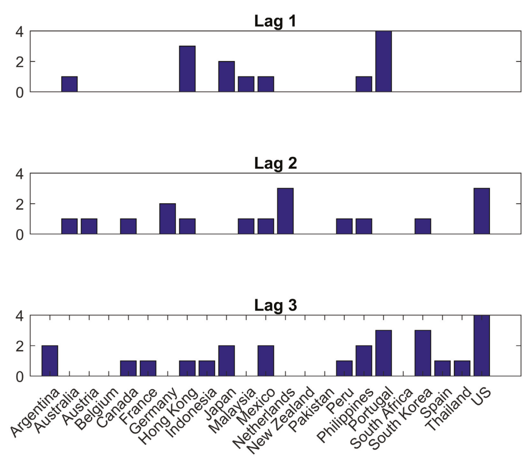
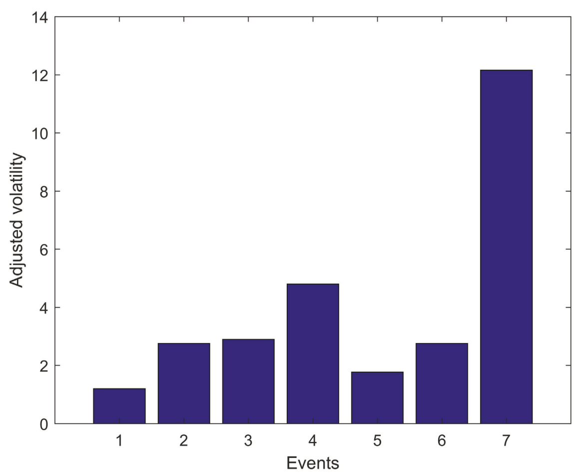


Figure 6. Results of the Granger causality tests after filtering for event 6.

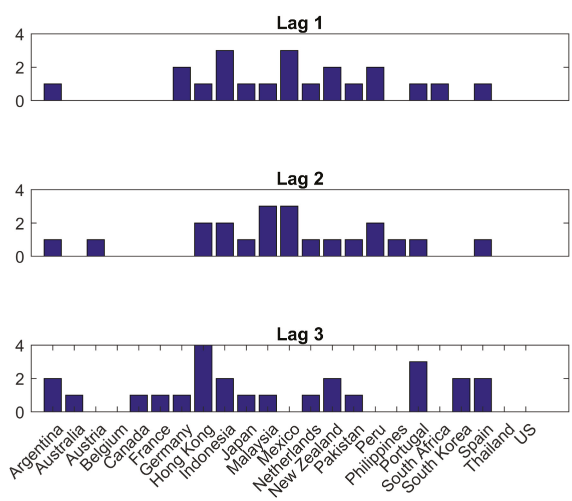
4.7. Event 7—3 September 1998

Event 7 was a rather important event with the replacement of the Malaysian finance minister. This event lead to a decades long feud among the Malaysian elites. As previously mentioned, Malaysia followed a rather unique direction during the crisis compared to its regional neighbors by refusing the bailout offered by the IMF. During event 7 most of the markets analyzed experienced a significant increase in volatility (Figure 7a). The case of Malaysia is particularly remarkable with volatility increasing to 12 times the base line levels.

This increase in adjusted volatility was much large in the case of Malaysia than in the case of its regional neighbors. Using one- and two-day lag there were 21 statistically significant Granger causality relationships while 25 relationships were found when using 3 days lag (Figure 7b). The Indonesian stock market during this period seemed to impact several other markets such as for instance Japan and the Philippines (using a lag of 1 day). The adjusted volatility for all the countries/jurisdictions and for all the seven events considered can be seen in Table A1. The main statistics for the indexes in 1996, which was used as a reference period to estimate the pre-existing (base) volatility of the indexes can be seen in Table A2. The main statistics for the indexes for all the events can be seen in Tables A3–A9 and the results form the Granger tests can be seen in Tables A10–A16. The null hypothesis in the Granger tests is that $Index_A$ does not Granger cause $Index_B$.



(**a**) Adjusted volatility for Malaysia during all the considered events



(**b**) Results of the Granger causality tests after filtering for event 7

Figure 7. Adjusted volatility for Malaysia and Granger analysis of event 7.

5. Discussion

When analyzing financial crises there is a tendency to consider the long term impacts on the economy with less attention to the short-term impacts on the equity market that are among the principal concerns for equity investors. Even if the equity market fully recovers after a financial crisis, the loss to equity investors might be very substantial. Equity investors might be forced to unwind the positions because risk management concerns or margin calls, even if they believe that the market is going to recover. This type of short-term fluctuations are sometimes neglected in the literature even if they might have very substantial economic impacts on investors.

While there is clearly some level of subjectivity, from a stock market point of view the South-East Asia financial market can be divided, according to the short-term event driven carried out, into three main phases. A first phase in which the crisis initially appears to be a local issue to then rapidly spread to other stock markets even outside Asia. This phase goes approximately from the decision of Thailand to float the baht on 2 July 1997 (event 1) to the collapse of Peregrine investments on 12 January 1998 (event 4). During this phase there is an increasing level of volatility, adjusted for base line effects, across stock markets. The number of statistically significant Granger causality relationships, adjusted for base line effects, also gradually increases. A second phase, of lower volatility across multiple stock markets happened during event 5 which was the release by Thailand of the new guidelines for non-performing bank loans on 31 March 1998. While volatility decreased during this period there are indications of contagion with the number of statistically significant Granger relationships increasing. This was a period of lower volatility that for some markets expanded to event 6. Event 6 was the victory of Joseph Estrada in the general elections of the Philippines on 11 May 1998. The final phase was another spike in volatility on 3 September 1998 when the Malaysian finance ministered was replaced triggering a spike in volatility across markets.

The results from F-test comparing the volatilities for each market during each event with its baseline levels of 1996 are consistent with above mentioned results. This analysis suggests that there were two differentiated peaks in stock market volatility one centered around the collapse of Peregrine investments (event 4) and another centered around the period when the finance minister in Malaysia was replaced (event 7). This second peak in volatility was, at least for some countries, even more intense that during the first phase of the crisis. During the period in which that Thai government released the new guidelines for non-performing loans classification (event 5) there were indications of contagion effects even outside Asia. There are, however, no statistically significant indications of a single country in South-East Asia having consistently driven (tested using Granger causality) the stock market of several other countries consistently during the entire crisis period.

It would be interesting, as a line of future research, to use machine learning techniques to model the stock prices during the Southeast Asia financial crisis. It remains unclear if machine learning techniques can handle black swan events such as the Southeast Asia financial crisis. Machine learning techniques use historical data to train the chosen algorithm, such as neural networks. If the behavior of the market during a financial crisis is new, i.e., the market has not experienced similar conditions in the past, the neural network might have problems generating accurate forecasts.

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Appendix A

Table A1. Adjusted volatility per jurisdiction in each event.

Event/Jurisdiction	Symbol	1	2	3	4	5	6	7
Argentina	X_1	0.853	0.728	2.485	1.700	0.960	1.114	4.063
Australia	X_2	0.928	1.076	2.322	1.566	0.689	0.972	1.908
Austria	X_3	1.120	2.120	2.849	1.802	1.240	1.043	3.653
Belgium	X_4	1.106	1.674	1.767	1.486	0.984	1.721	2.641
Canada	X_5	1.310	1.147	2.685	2.201	1.134	1.088	3.747
France	X_6	1.424	1.628	2.053	1.533	1.404	1.908	3.257
Germany	X_7	1.145	2.037	3.202	1.811	1.091	1.535	3.694
Hong Kong	X_8	1.337	1.543	4.288	4.069	1.176	1.502	3.217
Indonesia	X_9	0.691	2.202	2.295	4.769	1.997	3.195	2.692
Japan	X_{10}	1.036	1.594	1.827	1.940	1.766	1.033	2.403
Malaysia	X_{11}	1.207	2.759	2.899	4.803	1.771	2.761	12.159
Mexico	X_{12}	0.920	1.062	3.500	1.709	0.777	1.133	3.926
Netherlands	X_{13}	1.211	2.959	2.690	1.578	1.321	2.597	2.930
New Zealand	X_{14}	1.321	1.220	3.663	1.546	1.253	1.154	3.013
Pakistan	X_{15}	1.274	1.184	1.393	0.873	0.675	3.880	1.353
Peru	X_{16}	1.577	0.972	1.637	0.852	0.920	1.089	2.619
Philippines	X_{17}	2.814	3.162	1.984	4.135	0.901	1.708	3.860
Portugal	X_{18}	2.115	4.035	2.127	2.693	4.475	3.824	6.560
South Africa	X_{19}	0.496	1.158	3.591	2.531	1.015	2.573	4.145
South Korea	X_{20}	0.735	0.794	3.457	3.089	2.162	2.233	1.973
Spain	X_{21}	1.593	1.392	1.836	1.164	2.011	1.909	4.930
Thailand	X_{22}	2.244	2.037	2.286	3.601	0.722	1.625	2.016
United States	X_{23}	1.198	1.601	2.902	1.382	1.245	1.456	2.669

Table A2. Main descriptive statistics of the indexes in 1996 (used to calculate per-existing base volatility). Including the daily standard deviation σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.2250	0.0150	0.0009
Australia	0.1015	0.0075	0.0004
Austria	0.1693	0.0076	0.0006
Belgium	0.1949	0.0069	0.0007
Canada	0.2547	0.0061	0.0010
France	0.2205	0.0077	0.0008
Germany	0.2464	0.0079	0.0009
Hong Kong	0.3032	0.0103	0.0012
Indonesia	0.2300	0.0097	0.0009
Japan	−0.0125	0.0092	−0.0000
Malaysia	0.2262	0.0078	0.0009
Mexico	0.2089	0.0120	0.0008
Netherlands	0.2756	0.0073	0.0011
New Zealand	0.1092	0.0061	0.0004
Pakistan	−0.0118	0.0127	−0.0000
Peru	0.1525	0.0100	0.0006
Philippines	0.1809	0.0093	0.0007
Portugal	0.3100	0.0043	0.0012
South Africa	0.0060	0.0068	0.0000
South Korea	−0.1780	0.0126	−0.0007
Spain	0.3823	0.0077	0.0015
Thailand	−0.4924	0.0129	−0.0019
United States	−0.2910	0.0068	−0.0011

Table A3. Main descriptive statistics of the index (event 1). Including the standard deviation daily σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.0128	0.0329	0.0016
Australia	0.0069	−0.0116	−0.0006
Austria	0.0085	0.0769	0.0037
Belgium	0.0077	0.0707	0.0034
Canada	0.0080	0.0391	0.0019
France	0.0110	0.0798	0.008
Germany	0.0090	0.1170	0.0056
Hong Kong	0.0138	0.0786	0.0037
Indonesia	0.0067	0.0263	0.0013
Japan	0.0096	−0.0106	−0.0005
Malaysia	0.0094	−0.0690	−0.0033
Mexico	0.0110	0.1143	0.0054
Netherlands	0.0089	0.1317	0.0063
New Zealand	0.0081	0.0446	0.0021
Pakistan	0.0162	0.1624	0.0077
Peru	0.0158	−0.0143	−0.0007
Philippines	0.0261	−0.0329	−0.0016
Portugal	0.0091	0.0454	0.0022
South Africa	0.0034	0.0063	0.0003
South Korea	0.0093	−0.0572	−0.0027
Spain	0.0123	−0.0623	−0.0030
Thailand	0.0289	0.0618	0.0029
United States	0.0081	0.0378	0.0018

Table A4. Main descriptive statistics of the index (event 2). Including the standard deviation daily σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.0109	0.0223	0.0011
Australia	0.0080	−0.0411	−0.0020
Austria	0.0160	−0.0823	−0.0039
Belgium	0.0116	−0.1129	−0.0054
Canada	0.0070	−0.0418	−0.0020
France	0.0125	−0.0800	−0.0038
Germany	0.0161	−0.1040	−0.0050
Hong Kong	0.0159	−0.0691	−0.0033
Indonesia	0.0214	−0.3015	−0.0144
Japan	0.0147	−0.0888	−0.0042
Malaysia	0.0214	−0.2266	−0.0108
Mexico	0.0127	−0.0362	−0.0017
Netherlands	0.0217	−0.1009	−0.0048
New Zealand	0.0075	−0.0310	−0.0015
Pakistan	0.0151	−0.0219	−0.0010
Peru	0.0097	−0.0576	−0.0027
Philippines	0.0293	−0.1292	−0.0062
Portugal	0.0174	0.0342	0.0016
South Africa	0.0079	−0.0400	−0.0019
South Korea	0.0100	−0.0710	−0.0034
Spain	0.0107	0.0153	0.0007
Thailand	0.0262	−0.1447	−0.0069
United States	0.0109	0.0060	0.0003

Table A5. Main descriptive statistics of the index (event 3). Including the standard deviation daily σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.0373	−0.1225	−0.0058
Australia	0.0173	−0.1784	−0.0085
Austria	0.0215	−0.1280	−0.0061
Belgium	0.0122	−0.0861	−0.0041
Canada	0.0163	−0.0406	−0.0019
France	0.0158	−0.1170	−0.0056
Germany	0.0253	−0.1332	−0.0063
Hong Kong	0.0441	−0.4689	−0.0223
Indonesia	0.0223	−0.1922	−0.0092
Japan	0.0169	−0.0946	−0.0045
Malaysia	0.0225	−0.2167	−0.0103
Mexico	0.0419	−0.0831	−0.0040
Netherlands	0.0197	−0.0755	−0.0036
New Zealand	0.0224	−0.1586	−0.0076
Pakistan	0.0178	−0.0896	−0.0043
Peru	0.0164	−0.0733	−0.0035
Philippines	0.0184	−0.1195	−0.0057
Portugal	0.0092	−0.0711	−0.0034
South Africa	0.0245	−0.1210	−0.0058
South Korea	0.0436	−0.1327	−0.0063
Spain	0.0142	−0.0772	−0.0037
Thailand	0.0294	−0.1565	−0.0075
United States	0.0197	−0.0694	−0.0033

Table A6. Main descriptive statistics of the index (event 4). Including the standard deviation daily σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.0255	−0.0430	−0.0020
Australia	0.0117	0.0187	0.0009
Austria	0.0136	0.0241	0.0011
Belgium	0.0103	0.0601	0.0029
Canada	0.0134	0.0107	0.0005
France	0.0118	0.0450	0.0021
Germany	0.0143	0.0131	0.0006
Hong Kong	0.0419	−0.1315	−0.0063
Indonesia	0.0464	0.1985	0.0095
Japan	0.0179	0.1132	0.0054
Malaysia	0.0373	0.0382	0.0018
Mexico	0.0205	−0.0937	−0.0045
Netherlands	0.0116	0.0485	0.0023
New Zealand	0.0094	−0.0016	−0.0001
Pakistan	0.0111	0.1198	0.0057
Peru	0.0085	−0.0751	−0.0036
Philippines	0.0383	0.3920	0.0187
Portugal	0.0116	0.1235	0.0059
South Africa	0.0172	0.1566	0.0075
South Korea	0.0389	0.1813	0.0086
Spain	0.0090	0.0952	0.0045
Thailand	0.0464	0.4370	0.0208
United States	0.0094	0.0891	0.0042

Table A7. Main descriptive statistics of the index (event 5). Including the standard deviation daily σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.0144	0.0023	0.0001
Australia	0.0051	0.0428	0.0020
Austria	0.0094	0.0708	0.0034
Belgium	0.0068	0.0654	0.0031
Canada	0.0069	0.0492	0.0023
France	0.0108	0.0735	0.0035
Germany	0.0086	0.0967	0.0046
Hong Kong	0.0121	0.0226	0.0011
Indonesia	0.0194	0.0141	0.0007
Japan	0.0163	−0.0325	−0.0015
Malaysia	0.0137	−0.0547	−0.0026
Mexico	0.0093	0.0500	0.0024
Netherlands	0.0097	0.0516	0.0025
New Zealand	0.0077	0.0025	0.0001
Pakistan	0.0086	0.0244	0.0012
Peru	0.0092	0.0905	0.0043
Philippines	0.0083	−0.0121	−0.0006
Portugal	0.0193	0.0385	0.0018
South Africa	0.0069	0.0693	0.0033
South Korea	0.0272	−0.0981	−0.0047
Spain	0.0155	−0.0296	−0.0014
Thailand	0.0093	−0.1013	−0.0048
United States	0.0084	0.0225	0.0011

Table A8. Main descriptive statistics of the index (event 6). Including the standard deviation daily σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.0167	−0.1341	−0.0064
Australia	0.0073	−0.0488	−0.0023
Austria	0.0079	0.0310	0.0015
Belgium	0.0119	0.0438	0.0021
Canada	0.0066	0.0219	0.0010
France	0.0147	0.0848	0.0040
Germany	0.0121	0.0821	0.0039
Hong Kong	0.0155	−0.1281	−0.0061
Indonesia	0.0311	−0.0997	−0.0047
Japan	0.0095	−0.0134	−0.0006
Malaysia	0.0214	−0.1023	−0.0049
Mexico	0.0136	−0.0957	−0.0046
Netherlands	0.0190	0.0482	0.0023
New Zealand	0.0070	−0.0439	−0.0021
Pakistan	0.0495	−0.3572	0.0170
Peru	0.0109	−0.0330	−0.0016
Philippines	0.0158	−0.1701	−0.0081
Portugal	0.0165	−0.0105	−0.0005
South Africa	0.0175	0.1465	−0.0070
South Korea	0.0281	−0.0871	−0.0041
Spain	0.0147	−0.0018	−0.0001
Thailand	0.0209	−0.2713	−0.0129
United States	0.0099	−0.0303	−0.0014

Table A9. Main descriptive statistics of the index (event 7). Including the standard deviation daily σ, return, and average daily return.

Jurisdiction	Return	Daily σ	Avg. Daily Ret.
Argentina	0.0609	−0.2590	−0.0123
Australia	0.0142	−0.0441	−0.0021
Austria	0.0276	−0.2257	−0.0107
Belgium	0.0183	−0.1001	−0.0048
Canada	0.0228	−0.1235	−0.0059
France	0.0251	−0.1503	−0.0072
Germany	0.0291	−0.1717	−0.0082
Hong Kong	0.0331	0.0049	0.0002
Indonesia	0.0262	−0.3419	−0.0163
Japan	0.0222	−0.1006	−0.0048
Malaysia	0.0943	0.2068	0.0098
Mexico	0.0470	−0.0378	−0.0018
Netherlands	0.0215	−0.1893	−0.0090
New Zealand	0.0184	−0.1063	−0.0051
Pakistan	0.0173	0.1179	0.0056
Peru	0.0262	−0.2354	−0.0112
Philippines	0.0358	0.0189	0.0009
Portugal	0.0283	−0.2537	−0.0121
South Africa	0.0282	0.0518	0.0025
South Korea	0.0249	−0.0180	−0.0009
Spain	0.0381	−0.1394	−0.0066
Thailand	0.0260	0.1795	0.0085
United States	0.0181	0.0145	0.0007

Table A10. Granger test results—Event 1. Only combinations with p-value less than 5% shown.

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_1	X_{10}	0.0306		
X_1	X_{14}	0.0078		
X_2	X_{14}	0.0055		
X_7	X_{14}	0.0050		
X_9	X_3	0.0386		
X_{11}	X_{22}	0.0296		
X_{12}	X_6	0.0445		
X_{13}	X_1	0.0392		
X_{13}	X_{14}	0.0442		
X_{19}	X_{11}	0.0343		
X_{19}	X_{17}	0.0133		
X_{21}	X_{11}	0.0191		
X_{21}	X_{20}	0.0241		
X_{21}	X_{22}	0.0206		
X_1	X_{14}		0.0332	
X_2	X_{14}		0.0142	
X_7	X_{14}		0.0349	
X_7	X_{16}		0.0426	
X_{10}	X_{15}		0.0377	
X_{11}	X_3		0.0234	
X_{11}	X_{10}		0.0180	
X_{15}	X_5		0.0110	
X_{16}	X_9		0.0157	
X_{19}	X_{17}		0.0386	
X_{20}	X_{10}		0.0129	
X_{21}	X_{11}		0.0422	
X_{21}	X_{20}		0.0162	
X_{21}	X_{22}		0.0443	

Table A10. *Cont.*

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_3	X_{20}			0.0338
X_6	X_{14}			0.0457
X_6	X_{16}			0.0466
X_7	X_{16}			0.0347
X_9	X_{20}			0.0069
X_{11}	X_{10}			0.0295
X_{13}	X_1			0.0429
X_{15}	X_6			0.0409
X_{16}	X_9			0.0296
X_{17}	X_2			0.0244
X_{17}	X_{11}			0.0059
X_{17}	X_{15}			0.0373
X_{20}	X_{10}			0.0448
X_{21}	X_{20}			0.0119
X_{23}	X_{17}			0.0372

Table A11. Granger test results—Event 2. Only combinations with p-value less than than 5% shown.

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_3	X_2	0.0373		
X_3	X_{10}	0.0232		
X_9	X_5	0.0101		
X_9	X_{10}	0.0240		
X_{11}	X_{12}	0.0371		
X_{15}	X_{19}	0.0091		
X_{16}	X_8	0.0434		
X_{20}	X_{19}	0.0144		
X_{21}	X_{17}	0.0454		
X_{22}	X_8	0.0262		
X_{23}	X_{16}	0.0007		
X_1	X_{10}		0.0334	
X_6	X_5		0.0155	
X_6	X_{11}		0.0207	
X_8	X_2		0.0352	
X_9	X_3		0.0375	
X_9	X_5		0.0460	
X_9	X_{10}		0.0089	
X_{11}	X_1		0.0268	
X_{11}	X_{12}		0.0168	
X_{14}	X_{22}		0.0377	
X_{15}	X_8		0.0244	
X_{21}	X_{16}		0.0368	
X_{22}	X_8		0.0408	
X_{23}	X_{16}		0.0070	
X_8	X_2			0.0259
X_9	X_{10}			0.0280
X_{11}	X_{12}			0.0153
X_{14}	X_8			0.0313
X_{14}	X_{22}			0.0289
X_{16}	X_{21}			0.0272
X_{16}	X_{22}			0.0203
X_{22}	X_6			0.0139
X_{23}	X_{15}			0.0281
X_{23}	X_{16}			0.0299

Table A12. Granger test results—Event 3. Only combinations with p-value less than than 5% shown.

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_2	X_7	0.0151		
X_8	X_{12}	0.0206		
X_9	X_{12}	0.0191		
X_9	X_{14}	0.0309		
X_9	X_{15}	0.0257		
X_{11}	X_1	0.0064		
X_{11}	X_{12}	0.0011		
X_{12}	X_6	0.0434		
X_{18}	X_5	0.0443		
X_{19}	X_{15}	0.0107		
X_2	X_8		0.0478	
X_3	X_{15}		0.0035	
X_8	X_1		0.0264	
X_8	X_{23}		0.0391	
X_9	X_{15}		0.0201	
X_{10}	X_{14}		0.0054	
X_{11}	X_1		0.0005	
X_{11}	X_{12}		0.0040	
X_{13}	X_{15}		0.0178	
X_{19}	X_{15}		0.0012	
X_1	X_{16}			0.0325
X_2	X_7			0.0377
X_3	X_{14}			0.0292
X_3	X_{15}			0.0249
X_3	X_{23}			0.0189
X_7	X_{21}			0.0226
X_8	X_{23}			0.0360
X_9	X_{20}			0.0362
X_{11}	X_1			0.0029
X_{11}	X_6			0.0334
X_{11}	X_{12}			0.0160
X_{12}	X_{20}			0.0378
X_{14}	X_{22}			0.0161
X_{19}	X_{15}			0.0145
X_{20}	X_2			0.0296
X_{20}	X_9			0.0129
X_{21}	X_8			0.0151

Table A13. Granger test results—Event 4. Only combinations with p-value less than than 5% shown.

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_1	X_{14}	0.0067		
X_2	X_{19}	0.0331		
X_6	X_3	0.0139		
X_7	X_1	0.0233		
X_7	X_3	0.0377		
X_7	X_{11}	0.0488		
X_{12}	X_6	0.0152		
X_{15}	X_{20}	0.0377		
X_{16}	X_3	0.0397		
X_{16}	X_{14}	0.0141		
X_{20}	X_{21}	0.0410		
X_{22}	X_{20}	0.0157		
X_{23}	X_2	0.0387		
X_{23}	X_6	0.0414		
X_{23}	X_8	0.0022		
X_{23}	X_9	0.0337		

Table A13. *Cont.*

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_{23}	X_{11}	0.0122		
X_{23}	X_{14}	0.0007		
X_{23}	X_{16}	0.0069		
X_1	X_{14}		0.0054	
X_2	X_{19}		0.0196	
X_7	X_1		0.0134	
X_7	X_3		0.0376	
X_7	X_8		0.0019	
X_7	X_{12}		0.0210	
X_8	X_{19}		0.0418	
X_9	X_{14}		0.0244	
X_{14}	X_1		0.0216	
X_{20}	X_{15}		0.0243	
X_{23}	X_8		0.0039	
X_{23}	X_9		0.0046	
X_{23}	X_{14}		0.0034	
X_{23}	X_{16}		0.0199	
X_1	X_{12}			0.0006
X_1	X_{14}			0.0070
X_3	X_2			0.0371
X_3	X_{16}			0.0168
X_6	X_1			0.0350
X_6	X_3			0.0267
X_7	X_8			0.0088
X_7	X_{17}			0.0393
X_8	X_{11}			0.0483
X_{11}	X_8			0.0473
X_{16}	X_3			0.0286
X_{17}	X_3			0.0426
X_{20}	X_2			0.0216
X_{21}	X_{12}			0.0214
X_{21}	X_{18}			0.0059
X_{23}	X_8			0.0216
X_{23}	X_9			0.0065
X_{23}	X_{14}			0.0406

Table A14. Granger test results—Event 5. Only combinations with p-value less than than 5% shown.

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_1	X_{10}	0.0094		
X_1	X_{14}	0.0045		
X_1	X_{16}	0.0253		
X_2	X_3	0.0029		
X_2	X_7	0.0437		
X_3	X_2	0.0272		
X_3	X_5	0.0236		
X_7	X_{14}	0.0114		
X_8	X_5	0.0001		
X_8	X_{12}	<0.0001		
X_8	X_{14}	0.0234		
X_8	X_{16}	0.0069		
X_9	X_{15}	0.0039		
X_{12}	X_{10}	0.0131		
X_{12}	X_{16}	0.0010		

Table A14. *Cont.*

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_{14}	X_2	0.0489		
X_{14}	X_3	0.0007		
X_{14}	X_4	0.0022		
X_{14}	X_5	0.0113		
X_{14}	X_7	0.0038		
X_{14}	X_8	0.0056		
X_{14}	X_{10}	0.0195		
X_{14}	X_{11}	0.0103		
X_{14}	X_{12}	0.0108		
X_{14}	X_{16}	0.0063		
X_{16}	X_1	0.0106		
X_{16}	X_3	0.0044		
X_{16}	X_5	0.0085		
X_{16}	X_7	0.0407		
X_{16}	X_9	0.0436		
X_{16}	X_{10}	0.0451		
X_{16}	X_{12}	0.0175		
X_{16}	X_{20}	0.0020		
X_{23}	X_{15}	0.0471		
X_1	X_{10}		0.0258	
X_1	X_{12}		0.0360	
X_1	X_{14}		0.0141	
X_1	X_{16}		0.0055	
X_2	X_3		0.0145	
X_2	X_{16}		0.0490	
X_3	X_2		0.0361	
X_3	X_5		0.0213	
X_3	X_9		0.0119	
X_3	X_{10}		0.0403	
X_6	X_{10}		0.0006	
X_6	X_{11}		0.0279	
X_7	X_8		0.0248	
X_7	X_9		0.0483	
X_7	X_{12}		0.0328	
X_8	X_7		0.0023	
X_8	X_6		0.0406	
X_8	X_5		0.0011	
X_8	X_3		0.0405	
X_8	X_2		0.0041	
X_8	X_1		0.0001	
X_8	X_{16}		0.0075	
X_8	X_{14}		0.0017	
X_8	X_{12}		0.0001	
X_8	X_{10}		0.0187	
X_9	X_3		0.0154	
X_9	X_6		0.0320	
X_9	X_{15}		0.0252	
X_{11}	X_1		0.0316	
X_{11}	X_6		0.0149	
X_{11}	X_{13}		0.0278	
X_{12}	X_{10}		0.0159	
X_{12}	X_{16}		0.0071	
X_{14}	X_3		0.0208	
X_{14}	X_5		0.0335	
X_{14}	X_7		0.0253	
X_{14}	X_8		0.0069	
X_{14}	X_{10}		0.0392	
X_{14}	X_{11}		0.0225	
X_{14}	X_{16}		0.0130	

Table A14. *Cont.*

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_{16}	X_1		0.0319	
X_{16}	X_5		0.0466	
X_{16}	X_9		0.0364	
X_{16}	X_{17}		0.0347	
X_{16}	X_{20}		0.0107	
X_{20}	X_8		0.0483	
X_{22}	X_8		0.0209	
X_1	X_{14}			0.0114
X_1	X_{16}			0.0208
X_2	X_3			0.0299
X_2	X_{18}			0.0282
X_3	X_2			0.0366
X_3	X_9			0.0305
X_3	X_{10}			0.0085
X_3	X_{11}			0.0443
X_3	X_{14}			0.0342
X_6	X_9			0.0062
X_7	X_9			0.0435
X_7	X_{11}			0.0030
X_7	X_{12}			0.0005
X_7	X_{14}			0.0085
X_8	X_1			0.0004
X_8	X_2			0.0138
X_8	X_5			0.0008
X_8	X_7			0.0271
X_8	X_9			0.0167
X_8	X_{12}			0.0011
X_8	X_{14}			0.0304
X_8	X_{16}			0.0242
X_9	X_3			0.0164
X_{11}	X_9			0.0147
X_{12}	X_{16}			0.0011
X_{12}	X_{20}			0.0038
X_{16}	X_9			0.0172
X_{14}	X_{16}			0.0166
X_{16}	X_{17}			0.0481
X_{16}	X_{20}			0.0127

Table A15. Granger test results—Event 6. Only combinations with p-value less than than 5% shown.

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_2	X_{18}	0.0372		
X_8	X_7	0.0114		
X_8	X_{10}	0.0440		
X_8	X_{12}	0.0254		
X_{10}	X_{18}	0.0342		
X_{10}	X_{23}	0.0339		
X_{11}	X_3	0.0117		
X_{12}	X_2	0.0167		
X_{17}	X_{20}	0.0475		
X_{18}	X_5	0.0422		
X_{18}	X_6	0.0414		
X_{18}	X_8	0.0288		
X_{18}	X_{13}	0.0312		

Table A15. *Cont.*

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_2	X_{18}		0.0417	
X_3	X_{20}		0.0125	
X_5	X_{23}		0.0363	
X_7	X_1		0.0482	
X_7	X_{20}		0.0212	
X_8	X_5		0.0250	
X_{11}	X_5		0.0455	
X_{12}	X_{10}		0.0168	
X_{13}	X_1		0.0381	
X_{13}	X_{18}		0.0303	
X_{13}	X_{20}		0.0080	
X_{16}	X_{17}		0.0335	
X_{17}	X_{20}		0.0004	
X_{20}	X_{23}		0.0408	
X_{23}	X_6		0.0155	
X_{23}	X_{12}		0.0290	
X_{23}	X_{13}		0.0084	
X_1	X_{17}			0.0366
X_1	X_{19}			0.0364
X_5	X_{23}			0.0231
X_6	X_{20}			0.0463
X_8	X_5			0.0315
X_9	X_{15}			0.0116
X_{10}	X_{22}			0.0389
X_{10}	X_{23}			0.0003
X_{12}	X_{18}			0.0235
X_{12}	X_{23}			0.0354
X_{16}	X_{21}			0.0167
X_{17}	X_{20}			0.0035
X_{17}	X_{21}			0.0407
X_{18}	X_3			0.0122
X_{18}	X_6			0.0131
X_{18}	X_7			0.0351
X_{20}	X_3			0.0386
X_{20}	X_{19}			0.0431
X_{20}	X_{21}			0.0353
X_{21}	X_5			0.0121
X_{22}	X_9			0.0153
X_{23}	X_5			0.0459
X_{23}	X_6			0.0097
X_{23}	X_9			0.0267
X_{23}	X_{13}			0.0033

Table A16. Granger test results—Event 7. Only combinations with p-value less than than 5% shown.

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_1	X_{15}	0.0441		
X_7	X_1	0.0198		
X_7	X_3	0.0205		
X_8	X_{15}	0.0394		
X_9	X_1	0.0402		
X_9	X_{10}	0.0068		
X_9	X_{17}	0.0212		
X_{10}	X_1	0.0045		
X_{11}	X_9	0.0272		
X_{12}	X_{15}	0.0020		
X_{12}	X_{17}	0.0149		
X_{12}	X_{22}	0.0329		

Table A16. *Cont.*

$Index_A$	$Index_B$	Lag-1 p-Val.	Lag-2 p-Val.	Lag-3 p-Val.
X_{13}	X_3	0.0048		
X_{14}	X_{10}	0.0074		
X_{14}	X_{20}	0.0139		
X_{15}	X_{17}	0.0430		
X_{16}	X_8	0.0030		
X_{16}	X_{15}	0.0075		
X_{18}	X_{17}	0.0499		
X_{19}	X_{18}	0.0482		
X_{21}	X_{13}	0.0043		
X_1	X_3		0.0026	
X_3	X_{23}		0.0292	
X_8	X_{10}		0.0352	
X_8	X_{15}		0.0447	
X_9	X_1		0.0309	
X_9	X_{10}		0.0330	
X_{10}	X_1		0.0037	
X_{11}	X_1		0.0161	
X_{11}	X_8		0.0247	
X_{11}	X_{16}		0.0211	
X_{12}	X_{15}		0.0047	
X_{12}	X_{17}		0.0414	
X_{12}	X_{22}		0.0273	
X_{13}	X_3		0.0033	
X_{14}	X_{10}		0.0264	
X_{15}	X_{17}		0.0303	
X_{16}	X_9		0.0267	
X_{16}	X_{15}		0.0402	
X_{17}	X_{20}		0.0377	
X_{18}	X_{17}		0.0327	
X_{21}	X_{13}		0.0105	
X_1	X_3			0.0094
X_1	X_{15}			0.0456
X_2	X_{23}			0.0018
X_5	X_{23}			0.0173
X_6	X_{20}			0.0188
X_7	X_1			0.0480
X_8	X_6			0.0104
X_8	X_{10}			0.0050
X_8	X_{15}			0.0176
X_8	X_{16}			0.0334
X_9	X_1			0.0418
X_9	X_{10}			0.0292
X_{10}	X_1			0.0131
X_{11}	X_1			0.0121
X_{13}	X_3			0.0085
X_{14}	X_{20}			0.0449
X_{14}	X_{21}			0.0331
X_{15}	X_{17}			0.0043
X_{18}	X_9			0.0440
X_{18}	X_{15}			0.0111
X_{18}	X_{17}			0.0486
X_{20}	X_{21}			0.0380
X_{20}	X_{23}			0.0272
X_{21}	X_3			0.0477
X_{21}	X_{11}			0.0076

Table A17. Volatility F-test.

Index	Event 1	Event 2	Event 3	Event 4	Event 5	Event 6	Event 7
Argentina	0.40600	0.09510	0.00000	0.00012	0.88230	0.43960	0.00000
Australia	0.72540	0.58220	0.00000	0.00140	0.05150	0.93640	0.00000
Austria	0.42180	0.00000	0.00000	0.00001	0.13740	0.72650	0.00000
Belgium	0.46860	0.00019	0.00003	0.00520	0.99900	0.00008	0.00000
Canada	0.06200	0.33640	0.00000	0.00000	0.37470	0.53580	0.00000
France	0.13500	0.00046	0.00000	0.00250	0.01790	0.00000	0.00000
Germany	0.34240	0.00000	0.00000	0.00001	0.52620	0.00240	0.00000
H.K.	0.04450	0.00210	0.00000	0.00000	0.26050	0.00400	0.00000
Indonesia	0.05330	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Japan	0.75770	0.00085	0.00001	0.00000	0.00003	0.76890	0.00000
Malaysia	0.19300	0.00001	0.00001	0.00000	0.00003	0.00000	0.00000
Mexico	0.68820	0.00000	0.00000	0.00010	0.18160	0.37870	0.00000
Netherlands	0.18670	0.00000	0.00000	0.00110	0.05420	0.00000	0.00000
N.Z.	0.05430	0.16910	0.00000	0.00200	0.11970	0.31600	0.00000
Pakistan	0.09480	0.24230	0.02090	0.48380	0.04040	0.00000	0.03590
Peru	0.00120	0.94010	0.00039	0.40540	0.68790	0.53390	0.00000
Philippines	0.00000	0.00000	0.00000	0.00000	0.60080	0.00010	0.00000
Portugal	0.00000	0.00000	0.00000	0.00000	0.00000	0.00010	0.00000
S. Africa	0.00060	0.30700	0.00000	0.00000	0.85210	0.00010	0.00000
S. Korea	0.10500	0.22290	0.00000	0.00000	0.00000	0.00000	0.00000
Spain	0.00087	0.02110	0.00001	0.28990	0.00000	0.00000	0.00000
Thailand	0.00000	0.00000	0.00000	0.00000	0.08650	0.00048	0.00000
U.S.	0.21180	0.00075	0.00000	0.02440	0.13140	0.00830	0.00000

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Regime-Switching Determinants of Mutual Fund Performance in South Africa

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Abstract: This study assesses the effect of fund-level and systemic factors on the performance of mutual funds in the context of changing market conditions. A Markov regime-switching model is used to analyze the performance of 33 South African equity mutual funds from 2006 to 2019. From the results, fund flow and fund size exert more predictive influences on performance in the bearish state of the market than in the bullish state. Fund age, fund risk, and market risk were found to be the most significant factors driving the performance of active portfolios under time-varying conditions of the market. These variables exert more influence on fund performance under bearish conditions than under bullish conditions, emphasizing the flight-to-liquidity assets phenomenon and risk-aversion behavior of fund contributors during unstable conditions of the market. Consequently, fund managers need to maintain adequate asset bases while implementing policies that minimize dispersions in fund returns to engender persistence in performance. This study provides novel perspectives on how the determinants of fund performance change with market conditions as portrayed by the adaptive market hypothesis (AMH).

Keywords: fund performance; efficient market hypothesis; adaptive market hypothesis; behavioral finance; market conditions; Markov switching model

JEL Classification: G11; G14; G23

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1. Introduction

The investment focus of passive fund managers differs from active managers in terms of strategy and target clientele base. While passive management tracks the performance of a recognized market index or benchmarks, such as the New York Stock Exchange and the Johannesburg Stock Exchange, active management is premised on the ability to outperform the market (Cremers and Petajisto 2009; Cremers et al. 2016). However, drivers of fund performance could change with different market conditions, as suggested by proponents of the adaptive markets hypothesis (AMH) (Lo 2012; Al-Khazali and Mirzaei 2017). Explanations posited under the AMH suggest that the stability and efficiency of the financial markets in reflecting realistic values of financial assets is subject to change over time, and that investors and systemic fundamentals would adapt to prevailing conditions over the course of time (Lo 2012; Urquhart and McGroarty 2014). Consequently, the validation of AMH in the South African financial markets (Obalade and Paul-Francois 2018a, 2018b) suggests that the determinants of fund performance are subject to market conditions.

Evidence (S&P 2019) shows the prevalence of underperformance among fund managers in South Africa, where only 8.97% of active managers outperformed the market within five years (2014 to 2018). However, new investor assets continue to flow into the portfolios of fund managers, with over 1.9 trillion worth of assets under management as of the end of the second quarter of 2018 (Rangongo 2018). The mismatch between fund flow and performance results in the distortion of prices of assets and the efficiency of financial markets, which creates avenues for opportunistic traders to earn extraordinary returns. As a result, non-linear tools are required to test the dynamics of mutual performance, as much like other economic variables, the drivers of fund performance are subject to change over time.

However, the extant studies on mutual fund performance (Tan 2015; Arendse et al. 2018) were conducted in the context of stable market conditions, but these studies do not explain the enigmatic circumstances behind the increasing fund flows as against the continuous poor performance of mutual funds in South Africa, which can be explained by the current market conditions. In this context, the evaluation of the determinants of fund performance has to consider the dynamics of the market conditions because it provides additional analytical instrument for academics, investors, and industry practitioners who analyze mutual fund data for information and investment. Thus, this study makes significant contributions to the literature as the use of the Markov switching model in the forecasting of fund performance allows for regime dynamics to be accounted for to enable investors to achieve optimal returns on their investments relative to the associated risk of underlying assets.

The application of the Markov switching model in mutual fund performance analysis helps to measure the risk level in a given investment with two or more possible regimes or states of nature (De la Torre-Torres et al. 2020). Specifically, by knowing the probability of being in a given regime, an investor can determine whether to invest in a risky or riskless asset if the probability of being in a low volatility (bullish) or high volatility (bearish) regime of the market is high. Furthermore, a nonlinear analysis of the predictors of fund performance represents an important impetus towards eliciting explanations to incongruous flow-performance dynamics, explained in the preceding discussion. Moreover, the analysis of fund performance in the context of economic size provides additional perspectives on the effect of macroeconomic dynamics on fund performance under different market conditions. As a result, the main purpose of this study is to conduct a non-linear analysis of the determinants of South African mutual funds' performance under bullish and bearish market conditions through a Markov regime switching framework. The study's analysis tests the primary hypothesis that the dynamics of fund performance exert more predictive influences in the bullish state of the market than in the bearish state.

The remainder of the study is organized as follows: Section 2 presents the literature review, Section 3 presents the methodology and data sources, Section 4 discusses the estimation results of the empirical model, and Section 5 concludes.

2. Literature Review

Tan (2015) employs conventional measures of performance, namely the Sharpe, Treynor, Jensen's alpha, Treynor and Mazuy (TM), and Henriksson and Merton (HM) indices, to assess the performance of mutual funds in South Africa in terms of returns and market timing experts. The results of the study show that despite the South African financial system's resilience during the quantitative easing period after the global financial crisis in 2007/2008, most active managers recorded a benchmark trailing performance relative to optimal stock selection and market timing expertise. The conclusion of the study suggests a competitive fund stock market in South Africa post the global financial meltdown of 2007/2008, where less risk-bearing stocks generate similar returns, identical to high-risk ones. The findings of Tan (2015) generally provide insights about the determinants of mutual fund performance in South Africa.

However, the scope of the sample data (2009 to 2014) covering only the post-crisis period does not allow the dynamics of fund performance across different market conditions to be accounted for. Besides, the application of linear tests for the analysis of fund performance do not provide accurate explanations for the behavior of influencing factors of fund performance. This is because the dynamics of economic variables are subject to change to under different conditions. As a result, the use of nonlinear models, such as the Markov switching framework, which endogenously determines the different market regimes of a given time series, help to obtain more accurate inferences about the behavior of the influencing variables. Furthermore, the conventional performance measures employed in the analysis are prone to dynamic manipulation by fund managers (Qian et al. 2014). Hence, the reliance on these conventional metrics to test the performance of fund managers can lead to wrong conclusions about the performance of funds.

Arendse et al. (2018) investigated the generalized conclusion in the literature, intimating the existence of a positive relationship between the lagged performance of funds and the direction of subsequent fund flows in South Africa. The study employed a portfolio time-series technique, where funds were ranked according to their lagged performance over a period and grouped into quintiles. The evidence shows funds operating in emerging economies, such as South Africa, need to maintain superior performance momentum to sustain investor cash allocations to them. Additionally, the study documents that mutual fund contributors put more of a premium on funds' superior performance compared to their competitors than fund performance relative to the market. In this context, the study concludes that mergers of funds represent a plausible means of sustaining the growth of the industry in South Africa. Overall, the findings of Arendse et al. (2018) portray the direction of growth of the South African fund industry. However, their conclusions are inadequate in explaining the flow-performance asymmetries under different market conditions, as the relationship between fund flow and performance was tested with linear tools in this study.

Using the Carhart (1997) four-factor model, Huij and Post (2011) investigated performance persistence among mutual funds in emerging markets, which included South Africa. The conclusion of the study suggests that funds operating in emerging economies generally exhibit superior performance compared to their counterparts in the US. Like other emerging equity fund markets, the South African fund industry generally exhibits persistence in performance while differing significantly in characteristics from equity funds of the US market (Huij and Post 2011). However, recent evidence by Bertolis and Hayes (2014) shows that the South African equity fund industry is gradually filtering out of persistence in performance relative to their counterparts in other emerging markets. Nonetheless, the lack of persistence in the performance of funds in South Africa is inconsistent with the continuous flow of investor assets to fund managers.

As explained in Section 1, fund managers in South Africa underperformed in the market consistently over five years (2014–2018). The evidence shows that the average performance, in terms of realized returns of South African funds, underperformed the market index by 34.01% in one year, trailed it by 84.66% in three years, and significantly underperformed it by 91.03% in five years (S&P 2019). Nonetheless, the volume of new cash inflows into South African equity mutual funds increased, with over R2.2 trillion assets currently under management (Asisa 2020). This evidence implies the existence of a significant mismatch in the flow–performance relations given the increasing level of investor allocations and the cross-sectional average performance of South African funds.

Arendse et al. (2018) further demonstrated that fund managers and contributors in South Africa exhibit traits of convex reactions relative to fluctuations in stock prices, and the level of risk assumptions vis-à-vis access to market updates on stocks of active portfolios. This phenomenon can be linked to the findings of Popescu and Xu (2017), which suggest that risk-shifting tendencies among active fund managers are indicative of less exposure bearing activity during bear markets and aggressive investment activity during bull markets. In this context, nonlinear test tools are required to analyze the flow–performance relations to generate accurate inference about the behavior of these economic variables under changing market conditions. Largely, the extant research on mutual fund performance dynamics in South Africa is premised on linear prepositions and methodologies driven by the underlying explanations of the EMH, and hence they are unable to provide explanations of the inscrutable dynamics influencing the continuous inflow of investor cash to consistently underperforming fund managers in South Africa (Arendse et al. 2018; Huij and Post 2011; Tan 2015).

However, explanations posited under the AMH suggest that the interaction between economic variables, such as fund flow and performance, is unlikely to be the same under different market conditions, as their behaviors are subject to change over time (Lo 2012). Besides, individual markets experience varying predictability levels attributable to market conditions (Urquhart and McGroarty 2016) and hence, nonlinear modelling of the market dynamics is required to ascertain accurate conclusions about the behavior of economic variables, such as the performance of fund portfolios. Bojanic (2021) explained that Markov switching models are mostly employed for the analysis of macroeconomic and financial variables as the dynamics of these variables are subject to periodic and systemic fluctuations over time. Pastpipatkul et al. (2020) also affirmed that Markov switching models help to account for dynamic change in economic data because the economic factors exhibit varying levels of dependencies under different market conditions. As explained in Section 1, the application of the Markov switching model in mutual fund performance analysis helps to measure the risk level in a given investment with two or more possible regimes or states of nature. In this context, an investor can determine whether to invest in a risky or risk-free asset if the probability of being in a bullish or bearish regime is high.

Furthermore, explanations for the consistent underperformance of fund managers despite the continuous flow of investors' cash to them remain a gap in the literature that calls for an investigation. Moreover, with a projection of a significant rise in South African mutual fund assets due to a resurgence in stock investment in 2019 and beyond (Ziphethe-Makola 2017), knowledge of the influencing dynamics of performance under changing market conditions becomes an essential toolkit for fund contributors and fund managers for optimal investment decision-making. It is hypothesized in this study that fund-level and systemic factors exert more predictive influences on fund performance in bullish markets than in bearish market conditions.

3. Methodology

3.1. Data and Sample Selection

Quarterly data spanning from the end of first quarter of 2006 to the end of the last quarter of 2019 of 33 actively managed equity funds sourced from McGregor BFA Library, S&P Capital IQ, and the Association of Savings and Investment South Africa (ASISA) website were employed in this study. GDP data for economic size was sourced from the South African Reserve Bank's website. For a fund to be included, it should have six years of data for analysis and the sample period was determined by the availability of data. In calculating South African equity funds' performance, quarterly returns of the price index of funds were logarithmically computed. Following Rupande et al. (2019), fund performance by raw returns was formulated as:

$$\mathrm{R_{it}} = \ln\left(\mathrm{P_{it}}/\mathrm{P_{it-1}}\right) \times 100 \tag{1}$$

where $\mathrm{R_{it}}$ is the return on fund i in quarter t, $\mathrm{P_{it}}$ denotes the current price of fund i in quarter at t, $\mathrm{P_{it-1}}$ is the price of the fund in the previous period $t-1$, and ln is the natural logarithm of the price index.

Following Nenninger and Rakowski (2014), fund flow was computed as the net quarterly percentage of cash flows accruing to a fund as a result of investor stock purchasing and redemption activity. A fund's cash flow is expressed as:

$$\mathrm{Flow_{it}} = \left(\mathrm{TNA_{it}} - \mathrm{TNA_{it-1}}(1 + \mathrm{r_{it}})\right)/\mathrm{TNA_{it-1}} \tag{2}$$

where $\mathrm{Flow_{it}}$ is the total net assets of fund i at quarter t, $\mathrm{TNA_{it}}$ reflects the fund's total net assets at quarter t, $\mathrm{TNA_{it-1}}$ is fund i's total net assets for the previous quarter $t-1$ whereas r_{it} denotes fund *i's* return in quarter t that accounts for reinvested dividends and adjusted for the fund's overheads. Fund flow was included in the analysis as the main independent variable of interest because the literature suggests that funds that benefit from increased levels of cash flow generally perform better than funds that secured limited cash flow in the past (Rohleder et al. 2017).

3.2. Markov Switching Model for Determinants of Fund Performance under Bullish and Bearish Market Conditions

From the literature (Anas et al. 2007; Bilgili et al. 2012), Markov switching models are suitable for capturing the asymmetry and persistency in data with extreme values, while enabling accurate inference about the behavior of financial and economic variables within a nonlinear framework. Bilgili et al. (2012) attribute the extensive use of linear test tools in the analysis of financial data to the ready access to statistical software that are suited for predictive linear propositions. They explained that, notwithstanding the ability of linear models, such as bivariate or autoregressive integrated moving average (ARIMA), to account for the dynamics in economic and financial time series, their inability to capture dependency directions, volatilities, and asymmetries in the relationship of interacting variables remains a shortfall. However, Markov switching models enable parametric changes through stochastic innovations. In this context, fluctuations from bearish (high level volatility) to bullish (low level volatility) market conditions are accounted for through the estimation of the regime transition probabilities.

Prior studies (Gray 1996; Koy 2017; Ma et al. 2018) have applied the nonlinear econometric MS model of Hamilton (1989) for modelling nonlinear behavior of financial and macroeconomic time series. Fund performance, much like other economic variables, is subject to change over time and hence it requires nonlinear modelling to obtain accurate inferences about its behavior under different market conditions (Lo 2012). Kim (2004) explained that the Markov switching specification is appropriate for capturing the stylized dynamics of monthly and quarterly returns (Kim 2004). In addition, Markov-switching models define the market regimes endogenously, thereby avoiding the need to use instrumental variables and any data-mining concerns associated with doing so (Areal et al. 2013). Furthermore, Markov switching models account for possible structural breaks and regime changes in the behavior of economic variables, which allows for the estimation of the durations and probabilities of the innovations (Koy 2017). Although the use of high-frequency data allows for more data points for the regime switching analysis, the Markov switching model is applicable for the amount of quarterly data employed in this study, as Bilgili et al. (2012) employed quarterly data (spanning from the first quarter of 1988 to the second quarter of 2010) in Markov regime switching models to analyze the correlation between foreign direct investment (FDI) and a set of explanatory variables (11 variables in total).

Following Ma et al. (2018), a two-state Markov regime switching regression model (Hamilton 1989) was employed to estimate the determinants of performance (y_{st}) of individual funds in the cross-section. In this study, a two-state Markov switching model was estimated to ascertain how mutual fund performance is related to the set of explanatory variables employed in the analysis. Primarily, this model was estimated to capture and identify the effect of individual variables on fund performance under bullish and bearish conditions of the market. The adopted model is represented as follows:

$$y_{s_t} = \beta_{0,s_t} + \sum_{i=1}^{K} \beta_{i,s_t} x_{i,t} + \varepsilon_{s_t} \tag{3}$$

where x_i*'s* are factors affecting the performance of a fund. The indicator variable $s_t = 1$ or 2 denotes the two possible regimes' switching states, which are unobservable, and ε_{s_t} is the normally distributed error term with zero mean and standard deviation σ_{s_t} for each $s_t = 1,\ 2$.

All the coefficients and the error term ε_t are allowed switch between the two states (bullish and bearish). The transition probability from state 1(2) to state 2(1) over the time period t to t+1 is governed by the Markov transition probability $p_{12}(p_{21})$, which is assumed to be constant over time. The distribution of y_{s_t} is fully described by σ_{s_t}, β_{0,s_t}, β_{i,s_t}, p_{11}, and p_{12} and $0 < p_{11} < 1, 0 < p_{22} < 1$. The transition matrix P is therefore represented by:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{4}$$

where p_{11} + p_{12} = 1 and p_{21} + p_{22} = 1.

Given that uncertainty surrounds the state of the market s_t at any given time t, the state of the market s_t is inferred from the state of the market at time t. The possibility of having s_t at a given time t to be in regime j is given by:

$$\zeta_{jt} = Pr(s_t = j|\Omega_t; \theta) \tag{5}$$

where j = 1, 2, and Ω_t is the information observed from time 0 up to time t including both the dependent variables and independent variables and θ is the set of population parameters of the regime switching regression; that is:

$$\theta = (\beta_{i,1},\ \beta_{i,2},\ p_{11},\ p_{12},\ \sigma_1,\ \sigma_2)\prime \tag{6}$$

The regime of the state can either be 1 or 2. In this context, the two probabilities $\zeta_{1,t}$ and $\zeta_{2,t}$ always sum to 1. The probabilities can be inferred iteratively from t = 1, 2, ..., T. Under Gaussian assumption of the error terms for the two regimes, the conditional densities needed to perform the iteration are given by:

$$\eta_{j,t} = f(y_t|s_t = j,\ \Omega_{t-1};\ \theta) = \frac{1}{\sqrt{2\pi\sigma_j}} \exp\left[-\frac{(y_t - x_t'\beta_j')^2}{2\sigma_j^2}\right] \tag{7}$$

Thus, the conditional density of the observation is the probability weighted sum of both states, which is:

$$f(y_t|\ \Omega_{t-1};\ \theta) = \sum_{i=1}^{2}\sum_{j=1}^{2} p_{ij}\zeta_{1,t-1}\eta_{j,t} \tag{8}$$

The log likelihood function associated with the iteration is then:

$$Logf(\theta) = \sum_{t=0}^{T} \log f(y_t|\Omega_{t-1};\ \theta) = \sum_{t=0}^{T} \log\left(\sum_{i=1}^{2}\sum_{j=1}^{2} p_{ij}\zeta_{i,t-1}\eta_{jt}\right) \tag{9}$$

The parameters θ can be estimated by maximizing the log likelihood function of Equation (9).

To capture all the information available in the sample, the smoothed transition probabilities for the fluctuations in fund performance were estimated. This study follows Yu and Kobayashi (2006) based on the algorithm of Kim (1994) and mathematically represents the smoothed probabilities as:

$$P(S_t = i|S_{t+1} = j,\ \mathcal{Z}^T;\ \theta) \tag{10}$$

$$\approx P(S_t = i|S_{t+1} = j,\ \mathcal{Z}^t;\ \theta) \tag{11}$$

$$= \frac{P(S_t = i|S_{t+1} = j,\ \mathcal{Z}^t;\ \theta)}{P(S_{t+1} = j\ |\mathcal{Z}^t;\ \theta)} \tag{12}$$

$$= \frac{P_{ij}\ P(S_t = i|\mathcal{Z}^t;\ \theta)}{P(S_{t+1} = j\ |\mathcal{Z}^t;\ \theta)} \tag{13}$$

For i, j = 0, 1, thus the smoothed probabilities are given as:

$$P(S_t = i|\mathcal{Z}^T;\ \theta)$$

$$= P(S_{t+1} = 0|\mathcal{Z}^T;\ \theta)\ \ P(S_t = i|S_{t+1} = 0,\ \mathcal{Z}^T;\ \theta) + P\ (S_{t+1} = 1|\ \mathcal{Z}^T;\ \theta)\ P(S_t = i|S_{t+1} = 1,\ \mathcal{Z}^T;\ \theta) \tag{14}$$

$$\approx P(S_t = i|\ \mathcal{Z}^t;\ \theta) \times \left(\frac{P_{i0}|P(S_{t+1} = 0|\mathcal{Z}^T;\theta)}{P(S_{t+1} = 0|\mathcal{Z}^t;\theta)} + \frac{P_{i1}P(S_{t+1} = 1|\mathcal{Z}^T;\theta)}{P\ (S_{t+1} = 1|\mathcal{Z}^t;\theta)} \right) \tag{15}$$

Equation (16) depicts the model specification, where fund-level and systemic variables, namely fund flow, fund size, fund age, fund risk, market risk, and economic size, are employed as explanatory variables. The model is specified as follows:

$$PERF_{s_t} = \beta_{0,s_t} + \beta_{1,s_t}FLOW_{i,t} + \beta_{2,s_t}LNTNA_{i,t} + \beta_{3,s_t}LNAGE_{i,t} + \beta_{4,s_t}STDFND_{i,t} + \beta_{5,s_t}STDMKT_{m,t} + \beta_{6,s_t}ECOSIZE_{m,t} + \varepsilon_{s_t} \tag{16}$$

where $PERF_{s_t}$ is fund performance at time t and $FLOW_{i,t}$ is the total net assets of fund i at quarter t. Fund flow is included in the analysis as the main independent variable of interest because the literature suggests that funds that benefit from increased levels of cash flow generally perform much better than funds that secured limited cash flow in the past (Rohleder et al. 2017). Further, explanations posited in the smart money hypothesis suggest that fund contributors are able to distinguish between competent and incompetent fund managers, which informs their asset allocation decisions in favor of competent managers (Elton et al. 1996; Ferreira et al. 2013). In this context, it is generally expected that investor cash flows will exert a positive influence on the future performance of funds, although evidence suggests that the smart money hypothesis largely thrives on momentum as investors chase recent outperformers (Sapp and Tiwari 2004). $LNTNA_{i,t}$ denotes fund *i's* size in quarter t, which is measured as the natural logarithm of total net assets. This variable was included in the analysis to control for the growth potential of funds, as large funds are generally more challenging to grow (Sirri and Tufano 1998; Guercio and Reuter 2014).

However, large funds attract more attention in terms of cash flow from investors, which results in a superior performance in the long run (Goetzmann and Peles 1997; Kacperczyk et al. 2016). Furthermore, scholars have explained that the maintenance of large volumes of investor assets result in a host of trading opportunities for fund managers (Ferreira et al. 2013). Evidence has shown that unlike small funds, large mutual funds benefit from economies of scale as they are able to minimize the per unit cost associated with their transactions and operations, while achieving optimal trading results (Ferreira et al. 2012, 2013). $LNAGE_{i,t}$ is the age of fund i at quarter t measured as the natural logarithm of the fund's age in years. From the literature, the age of funds affects their overall performance as investors' decisions on mutual funds are affected by the number of years a given fund has been in operation as older funds generally grow more slowly than younger funds (Del Guercio and Tkac 2002; Pástor et al. 2015). As a result, this variable was incorporated in the analysis to control for the effect of fund age on performance.

Following the formulation of Xiao et al. (2014), $STDFND_{i,t}$ represents fund *i's* portfolio risk at quarter t, and is measured as the standard deviation of a fund's monthly returns from quarter $t-4$ to quarter $t-1$. This approach allows for the calculation of the annualised standard deviation (rate of dispersion) of fund returns in the past 12 months, and hence the riskiness of a fund's portfolio. From the literature, the average investor is generally sensitive to the risk associated with an investment and takes it into consideration when making decisions on mutual funds, as fund risk adversely impacts their performance (Huang et al. 2012; Xiao et al. 2014). $STDMKT_{m,t}$ denotes market risk in quarter t, which is measured as the standard deviation of the stock market's daily returns from quarter $t-4$ to quarter t–1. This method allows for computation of the annualized standard deviation of the daily returns of the stock market in the past trading year, to determine the overall risk of the equity market. Scholars have explained that stock market volatility affects investors' decision on mutual funds, as investor skepticism about expected returns vis-à-vis the system risk increases under conditions of uncertainty (Barber et al. 2016; Kim 2019). $ECOSIZE_{m,t}$ denotes the economic size (proxied by gross domestic product–*lgdp*) of the market in which fund i operates at quarter t. From the literature, the performance of mutual funds is linked to the direction of growth of the economy within which funds operate, where macroeconomic expansions impact positively on fund returns while economic contractions deteriorate the returns of funds (Ferreira et al. 2012; Fuerst and Matysiak 2013; Gueddoudj 2018).

In the analysis, a two-state regime switching regression model was used, where all coefficients and error terms are allowed to take on different values in the two states denoted by S_t. A bullish market condition is characterised by a general increase in market returns and low volatility, while a bearish market condition refers to the period of a downward spiral in market returns and high volatility. The adopted regime switching model was estimated for each fund in the sample. Eviews 12 software was used for the estimation of the empirical model.

3.3. Normality Tests

A normality test was conducted to analyze the sample data with a non-normal distribution for the results of the specified nonlinear model to be valid (Schmidt and Finan 2018; Tsagris and Pandis 2021). All the variables report some negative asymmetry in their dynamics (skewness) and none of the variables report a value of zero. Besides, all the seven interacting variables employed in the analysis show excess kurtosis across the sampled funds, as their reported kurtosis values were either below or above three. As a result, the Jarque-Bera (JB) tests reject the hypothesis of normal distribution. Consequently, non-normality is not a problem in the estimated models. It could be concluded that the results generated are valid in providing explanations to the dynamics of fund performance under different market conditions. The results of the normality test can be seen as Table S1.

3.4. Unit Root Tests

The presence of non-stationary explanatory variables is likely to lead to spurious regression when the MS model parameter is estimated (Granger and Newbold 1974). To resolve this problem, the augmented Dicky Fuller (ADF) was employed to check for the presence of unit roots for each selected variable for each fund in the sample. The ADF test shows that the variables employed in the analysis are all stationary across sampled funds. The unit root test results can be seen as Table S1.

4. Estimation Results and Discussion

4.1. Descriptive Statistics of Fund Performance

Table 1 summarizes the descriptive statistics of the levels of quarterly performance of the 33 sampled funds for the period March 2006 to end of 2019. From the table, the performance varied considerably across the funds, with IP HIGH fund being the lowest (with a mean value of -0.927) and Stanlib fund being the highest (with a mean value of 4.012). The variation in the performance of each fund during the period under study appears to be significant as can be observed from the large difference between the maximum and minimum performance values. The variation in cross-sectional performances is largely linked to the period of financial meltdown in 2007 and 2008, where it is found to be more evident. Moreover, the performance of the funds shows several negative asymmetries in their dynamics (skewness) and excess kurtosis is reported across the sampled funds, implying that the performance of the sampled funds is not normally distributed. In this context, it can be explained that the performance of the sampled funds lacked stability.

Table 1. Descriptive statistics of fund performance.

Fund	Mean	Medium	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
Afena	1.921	2.857	8.594	−8.004	3.440	−0.933	3.393
Allan Gray	2.107	1.848	16.238	−14.326	5.218	−0.304	4.135
4D BCI	2.160	1.856	11.966	−4.688	3.317	0.151	3.304
3LAWS	−0.073	1.000	5.000	−7.000	3.199	−0.468	2.154
3600ne	3.666	5.000	12.000	−16.000	5.548	−1.055	4.249
Aluwani	3.549	3.022	15.664	−6.487	5.780	0.108	2.240
Analytics	2.232	3.449	6.953	−6.934	2.982	−1.317	4.266
Anchor	2.877	4.207	12.028	−6.939	3.592	−0.376	3.540
Blue Alpha	1.864	2.423	9.873	−7.095	3.813	−0.055	2.582
Bridge	3.469	4.030	12.029	−6.939	3.574	−0.539	2.235
Cannon	1.162	1.068	16.058	−9.937	5.517	0.554	3.631
Capita BCI	1.427	1.708	3.604	−3.479	1.435	−1.509	6.067
Centeaur	2.779	4.186	15.415	−15.706	6.282	−0.890	4.182
Clucasgray	0.789	0.686	10.431	−6.164	2.836	0.394	4.558
Counterpoint	0.553	0.644	4.478	−3.746	1.535	−0.081	3.853
Dalebrook	0.275	0.290	6.301	−7.118	3.068	−0.415	3.332
Denker	0.363	0.389	4.478	−3.746	1.565	0.196	3.626
Graviton	1.699	2.276	3.360	−3.619	1.454	−1.656	5.738
GTC	0.114	0.038	6.454	−6.899	2.618	0.034	4.161
Harvard	0.006	0.103	6.241	−10.738	2.605	−1.347	7.701
Huysamer	0.459	−0.157	8.651	−11.155	3.779	−0.183	3.450
Imara	2.288	2.546	9.746	−8.524	3.716	−0.381	3.564
IP HIGH	−0.927	−1.034	8.499	−7.946	2.905	0.562	4.427
Kagiso	3.382	3.595	25.093	−9.032	6.054	0.895	4.998
Maestro	0.484	0.205	7.343	−10.719	3.479	−0.587	3.919
Naviga	−0.092	−0.141	6.285	−6.419	2.259	−0.007	4.959
Northstar	2.462	2.364	15.992	−8.701	3.733	0.808	6.745
Personal Trust	−0.286	0.078	8.980	−9.588	3.139	−0.381	5.003
RCI	1.539	2.870	10.244	−12.306	4.598	−1.031	4.144
RECM	1.238	2.146	14.368	−15.618	4.907	−0.922	5.689
Stanlib	4.012	4.045	13.084	−5.799	4.374	−0.093	2.529
ABSA Prime	3.410	3.520	13.083	−5.798	4.089	0.104	2.728
Prescient	3.792	6.101	9.240	−6.935	4.582	−0.929	2.401

Source: Authors' estimations (2021).

4.2. Discussion of Markov Regime Switching Regression Results of Fund Performance Determinants

Table 2 presents a summary of the Markov regime switching regression (Equation (16) results of fund performance determinants for sampled funds. The first row of each fund reports the estimated coefficients for the bullish Markov state and the second row reports those of the bearish state.

Table 2. Markov regime switching regression results summary of fund performance determinants.

Fund	Intercept	FLOW	LNTNA	LNAGE	STDFND	STDMKT	ECOSIZE
Afena	11.938 *** 5.479 ***	−0.072 0.224 ***	0.058 −1.232 ***	−2.068 *** −0.818 ***	−643.486 *** −93.279	−0.706 ** −0.205	−0.127 ** −0.099
Allan	2.078 12.712 ***	−0.034 −0.062 **	0.709 *** −0.513 ***	−2.204 *** −2.534 ***	71.376 97.015	−2.151 *** −2.338 ***	−0.142 ** 0.048
4D BCI	8.924 *** 1.086	0.106 −0.007	0.296 −0.177	−2.805 *** 0.338	−35.376 103.763 *	−4.034 *** −0.566	0.058 −0.010
3LAWS	12.113 15.862 ***	0.057 −0.001	−0.706 1.052 ***	−6.016 −10.195 ***	80.598 −152.805 ***	−5.656 *** −0.935 ***	0.439 * −0.076
360One	23.914 *** 13.486 ***	0.464 0.091	0.124 −1.709	−9.207 −0.055	−2167.139 *** −1204.542 ***	0.331 4.485 **	−1.099 −0.426
Aluwani	6.600 *** −3.635 *	0.009 *** −0.001	−0.717 * 0.435	−0.556 ** −0.454 *	118.190 120.512 ***	−2.124 −2.298 ***	−0.007 0.063
Analytics	20.298 *** −1.609	−0039 ** −0.009 ***	−1.267 *** 0.123	−4.964 *** 0.644	55.642 0.685	−0.418 0.223	0.027 0.167
Anchor	9.284 *** 12.411 ***	−0.017 0.287 ***	−0.547 −1.103 ***	−0.360 0.746 ***	−534.978 *** −601.861 ***	−0.353 −3.639 ***	0.018 0.139 ***
Blue Alpha	3.816 17.628 ***	0.019 0.014 **	0.042 −3.062 ***	−2.015 * −0.095	51.544 *** −204.309 ***	−0.344 8.387 ***	−0.307 −0.015
Bridge	41.411 *** 51.252 ***	0.033 −0.244 ***	−4.758 *** −4.366 ***	−1.126 −1.292 ***	−872.245 *** −711.282 ***	1.017 −12.949 ***	0.705 −1.321 ***
Cannon	29.533 *** −10.563 ***	0.275 −0.479 ***	−2.791 3.859 ***	−25.581 *** 2.836	1035.957 * −405.872 ***	−23.252 *** −6.390 ***	−0.635 −0.064
Capita BCI	6.100 *** −0.488	0.037 0.013	−0.852 −0.026	−0.812 *** 0.048	−596.041 *** 372.714 ***	−3.136 *** 0.071	0.012 0.008
Centeaur	5.220 *** 7.291 ***	−0.058 −0.216 ***	−0.134 0.379	−0.681 −2.770	119.551 *** −162.205 ***	−1.783 *** −2.238 ***	0.126 −0.433 ***
Clucas.	3.427 *** 1.814	−0.227 *** −0.156 ***	−0.143 −0.013	−1.043 *** 0.375 **	13.954 −77.569	−0.346 −0.216	−0.168 *** −0.017
Counter.	−0.797 1.314 ***	0.017 *** 0.008 *	0.174 −0.125	−0.664 0.454 ***	102.463 *** −11.537	−0.895 −0.349 ***	0.077 0.029
Dalebrook	−2.834 * 7.903 ***	0.006 *** −0.014 ***	0.602 *** −0.661 ***	0.125 −1.338 ***	−27.726 −390.159 ***	0.597 −1.407 *	−0.044 0.794 ***
Denker	1.302 −4.237 ***	0.003 −0.002	−0.169 −0.241	0.406 *** 0.459	4.206 635.442 ***	−0.251 −0.425 *	0.014 0.215 ***
Graviton	4.633 1.365 ***	0.069 0.008	−0.017 −0.091 ***	−0.909 0.105	−209.823 29.489	−1.718 *** 0.017	0.134 ** 0.025 ***
GTC	24.858 21.647 ***	−0.034 −0.030 ***	−2.135 * 1.434 ***	−4.037 −6.902 ***	−632.123 * −223.809 ***	−8.683 *** 1.551 *	−0.251 0.148
Harvard	−1.953 −3.216 **	−0.127 *** 0.043	2.457 *** 1.214	−0.191 0.826 ***	−466.652 *** −21.239	0.682 * 0.336	0.256 0.093
Huysamer	−4.197 0.810	0.136 *** 0.012	2.598 *** −0.995	0.038 0.446	54.873 * 21.280	−1.054 0.481	0.088 0.350 ***
Imara	−5.442 * 1.340	0.006 * −0.001	2.104 *** 0.911 *	0.802 −0.154	−237.013 *** −181.277 ***	1.003 *** 0.347	0.089 −0.001
IP HIGH	11.217 28.931 ***	0.007 0.002	−4.816 −19.534 ***	−1.721 *** 5.988 ***	−370.190 ** −268.682 ***	0.739 5.809 ***	−0.033 0.850 ***
Kagiso	7.737 *** 7.358 ***	0.038 −0.037 ***	−0.561 −0.469 ***	−1.207 −1.242 ***	15.936 137.428 ***	−5.123 *** −3.951 ***	−0.252 ** −0.125 ***

Table 2. *Cont.*

Fund	Intercept	FLOW	LNTNA	LNAGE	STDFND	STDMKT	ECOSIZE
Maestro	4.174 *** 1.042	−0.325 *** 0.123 ***	0.921 *** −0.452 ***	−2.969 *** 0.723	−130.129 −254.010	−0.124 2.430 *	0.267 * −0.180
Naviga	3.042 −6.046 ***	−0.019 * −0.220 ***	−0.226 2.355 ***	−0.886 * −1.827 ***	100.498 617.188 ***	−0.778 −6.677 ***	−0.486 3.208 ***
Northstar	7.624 *** 7.459 ***	−0.009 0.069 ***	2.225 ** 4.282 ***	−3.485 *** −5.145 ***	123.799 −3.175	−0.355 −0.759 ***	−0.089 * 0.102 ***
Personal Trust	−1.082 −4.345 ***	0.053 *** −0.001 ***	1.767 * 2.867 ***	−0.487 −0.831 ***	−58.519 28.875	−0.485 −0.813 ***	−0.238 −0.218 ***
RCI	46.592 * 48.343 ***	0.007 0.053 ***	−14.441 −18.791 ***	−10.574 * −11.566 ***	−69.376 −791.605 ***	−4.146 *** 1.157 ***	−1.116 2.643 ***
RECM	0.433 −0.535	−0.072 0.058 *	0.619 0.129	−1.366 0.416 ***	−379.661 *** 108.669 ***	2.130 ** −0.130	−0.425 * −0.066
Stanlib	18.676 *** 32.022 ***	−0.039 0.039	−3.532 * −5.235 ***	2.503 1.834 ***	−342.103 −704.414 ***	8.067 3.089 ***	−0.206 0.307 ***
ABSA	14.788 *** 33.219 ***	−0.001 0.024 ***	−1.801 −0.404	−1.665 −6.777 ***	−369.628 −784.171 ***	3.493 −1.549	0.035 −1.269 ***
Prescient	5.137 9.116 ***	0.004 −0.028 ***	9.511 *** 13.604 ***	−6.716 *** −9.491 ***	−433.241 −973.846 ***	3.344 8.023 ***	0.144 −0.384 ***

Note: *, **, and *** denote 10%, 5%, and 1% levels of statistical significance respectively. Source: Authors' estimations (2021).

From Table 2, it can be observed that fund-level and systemic variables exert varying influences on fund performance across bullish and bearish market conditions. Fund flow reports more significant relationships (23: 10 positive and 13 negative values) with performance across funds in the bearish state of the market, as against 10 (six positive and four negative values) significant coefficients in the bullish state. This result shows that fund flow, under the regime switching environment, exerts more influence on performance under bearish conditions of the market than under bullish market conditions. The results thus indicate that the high sensitivity of fund flow to performance in the bearish market is more in the negative terms than positive. This evidence is consistent with the position of the extant literature. Kosowski (2011) applied a Markov switching approach to analyze the determinants of fund performance and found that the effect of fund flow on performance is more evident in the bearish regime of the market than in the bullish regime. The study documents a negative predictive power of fund flow over performance, and explains that overtrading on the part of recent outperformers with enhanced investor cash allocations results in operational overruns that are not appropriately compensated for due to an increase in market volatility.

The results of Papadimitriou et al. (2020) also verify that the flow–performance relationship is more pronounced under bearish market conditions than bullish conditions. Moreover, Franzoni and Schmalz (2017) explained that investor risk-aversion tendencies and skepticism about fund performance during lower periods of the market tend to be more informative about managers' trading skill, compared to performance during upper periods of the market. However, Xiao et al. (2014) found that the sensitivity between fund flow and performance is more evident in the bullish state of the market than in the bearish state. They explain that generally, the effect of fund flow on performance is positive under changing market conditions and attribute this state of interaction to an increase in investor confidence in the trading skills of fund managers in bullish market conditions than in bearish conditions.

From Table 2, fund size (proxied by the natural logarithm of total net assets) reports more significant coefficients (20: 8 positive and 12 negative values) across the sampled funds in the bearish state than in the bullish state (13: eight positive and five negative values). This result implies that the influence of fund size on performance is more evident under bearish market conditions, and it is generally adverse under bullish conditions. From the literature, it is suggested that investor decisions regarding mutual funds are affected by fund size as large funds are generally more challenging to grow (Chevalier and Ellison 1997; Sirri and Tufano 1998; Xiao et al. 2014). Given that bearish market conditions are generally characterized by increased volatility and uncertainty around expected returns on underlying investment, it is expected that investor attention will focus more on the disadvantages associated with the acquisition of large funds' stocks (Chou and Hardin 2014). Similarly, through the application of a regime switching framework, Badrinath and Gubellini (2012) found that on a comparative basis, small funds are able to achieve higher returns than large funds under changing market conditions, which is more evident in bearish conditions of the market. However, the regime switching results of the drivers of fund performance by Chung et al. (2014) show that the predictive power of fund size over performance is more pronounced in the bullish state of the market than in the bearish state. Their finding links the effect fund size on performance to positive investor sentiments of fund managers' trading expertise. They explain that skepticism about the pace of growth of a fund is given minimal consideration by investors during stable market conditions, and hence they allocate more cash to large funds with the expectation of benefiting from wider investment opportunities.

The fund age variable (proxied by the natural logarithm of fund age in years) shows a more significant relationship with performance in the bearish state (21 significant coefficients: 14 positive and 7 negative values) than in the bullish state (16 significant coefficients: 1 positive and 15 negative values) across the sampled funds. Given that the significant relationship between fund age and performance is generally positive, it suggests that investors' cash allocation decisions on mutual funds are largely in favor of old and more established funds. However, the Markov switching results of fund performance determinants by Stafylas and Andrikopoulous (2019) suggest that young funds are generally able to sustain superior performance momentum during market downturns compared to their older counterparts. Similarly, evidence from other studies (Pástor et al. 2015; Rao and Tauni 2016) indicates that investor decisions on mutual funds favor younger funds, as older funds grow at a slower pace than younger funds. Meanwhile, the findings of a regime switching analysis of fund performance link the time-varying effect of fund age on performance to investor sentiments (Chung et al. 2014). The study explained that the effect of investor sentiment on fund performance is more pronounced in the bullish state of the market than in the bearish regime when it is driven by considerations premised on fund age and the ability to expand rapidly.

From Table 2, it can be observed that the influence of fund risk (proxied by the annualized standard deviation of funds monthly) on performance is generally pronounced in the bearish state (23 significant coefficients: 8 positive and 10 negative values). The bullish regime reports 15 significant coefficients (5 positive and 10 negative values). This result is expected because increased variability in fund returns tends to diminish investor confidence in fund managers' ability to generate utility for investors, as the literature (Li et al. 2013) suggests that mutual fund contributors take portfolio risk into consideration when making stock-picking decisions on mutual funds. In this context, the performance of funds with significant levels of risk are adversely affected as minimal investor assets accrue to them. However, Chung et al. (2014) obtained Markov switching results for the effect of fund risk on performance under changing market conditions. Much like the evidence found for fund age, their results link the time-varying effect of fund risk on performance to investor sentiments. They explained that the average investor becomes less skeptical about fund return variability when market conditions are less volatile, regardless of the direction of the fund manager's recent performance.

From the table, it can be observed that the market risk (proxied by the annualized standard deviation of daily returns of the equity market) exhibits a more significant relationship with performance in the bearish state (22 significant coefficients: 7 positive and 15 negative values) of the market than in the bullish state (13 significant coefficient: 2 positive and 11 negative values) across the sampled funds. This result suggests that generally, increased market volatility leads to significant deterioration of fund performance under time-varying conditions of the market. Through a Markov switching analysis, Turtle and Zhang (2012) found that the performance of funds operating in markets dominated by significant volumes of foreign investments tends to experience instability in performance as their activities are prone to the effects of fluctuations in external markets. Their evidence suggests that the performance of funds operating in emerging markets like South Africa experiences significant improvements in returns during periods of positive trends in the returns of advanced markets. These dynamics represent a spill-over market risk, which exerts significant impacts on the performance of emerging market funds as a result of their dependence on foreign investment. Intuitively, an increase in the dispersion of benchmark returns adversely impacts fund portfolios, as fund portfolios with significant components of its underlying investments deposited in exchange traded instruments are affected. Scholars have explained that investors' cash allocation decisions on mutual funds are influenced by market risk, which, in turn, affects funds' overall performance (Kim 2019; Barber et al. 2016).

As can be observed from the table, economic size shows a strong predictive influence on mutual fund performance under bearish market conditions (17 significant coefficients: 11 positive values and 6 negative values) than under bullish conditions (8 significant coefficients: 2 positive and 6 negative values). This evidence implies that generally, funds operating in large economies are able to perform better than their counterparts in smaller economies during periods of market downturns. This result is plausible because bigger economies present wider and more diverse trading opportunities for fund managers to relocate underlying investments in times of market meltdown to enhance performance. Kosowski (2011) applied the Markov switching approach to analyze the effect of economic fluctuations on fund performance and document that funds generally achieve more enhanced returns during periods of economic recession than expansion. Fund contributors thus exploit the time-varying risk-adjusted returns by allowing for predictability in performance. The study explained that fund contributors are able to benefit from predicted returns in this context because active managers are able to achieve significant excess returns during the contraction phase of the economy. In general, scholars agree that the performance of mutual funds is tied to the general well-being of the economy within which they operate (Ferreira et al. 2013; Fuerst and Matysiak 2013; Gueddoudj 2018). This appears to be the case in South Africa, indicating that stable economic growth is fundamental to the creation of a conducive environment for the growth of the South African fund market. Moreover, from the analysis, it can be observed that all the variables employed in the analysis exert more significant impacts on fund performance in the bearish state of the market than in the bullish. As a result, the study's hypothesis that the impact fund-level and systemic factors on mutual fund performance are more pronounced in the bullish state than in the bearish state is rejected as per the results in Table 2.

Table 3 shows the average of the coefficients of these three variables (obtained from running the estimated regime-switching model of Equation 16 of the funds in the sample). The cells labelled S1 and S2 consist of results for the bullish and bearish states, respectively. The three variables are *LNAGE*, *STDFND*, and *STDMKT*. The discussion of the most significant explanatory variables follows the presentation of the results in Table 3 for ease of reference.

Table 3. Cross-sectional analysis of the most significant explanatory variables.

	Variable					
Regime	***LNAGE***	**No. of Funds**	***STDFND***	**No. of Funds**	***STDMKT***	**No. of Funds**
S1	−4.249 ***	16	−358.263 ***	15	−2.563 ***	13
S2	−2.327 ***	21	−286.371 ***	22	−0.876 ***	21

Note: *** denotes a cross-sectional average statistical significance level at 1%. Source: Authors' estimation (2021).

4.3. Cross-Sectional Analysis of the Most Significant Explanatory Variables

From the empirical analysis in the previous section (Section 4.2), it can be observed that all the explanatory variables have an impact on the performance of mutual funds in South Africa, where fund-level and systemic variables show greater influence in market downturns than in upturns. In addition, significant differences are observed among the sampled funds in terms of the extent to which these explanatory variables are linked with a fund's performance. To ascertain the determinants of these cross-sectional differences, the three most significant explanatory variables were selected to conduct the cross-sectional analysis based on the regression results of Equation (16) as shown in Table 2.

The average coefficient of *LNAGE* for the cross-section of sampled funds in the bullish state (S1) is −4.24, which is composed of 16 funds with an average statistical significance at 1%. In the bearish state (S2), the average coefficient of *LNAGE* for the cross-section of funds is −2.327, which comprised 21 funds of the study sample and an average statistical significance at 1%. This evidence shows that fund age generally has a larger impact on fund performance in the bearish market (S2), which is consistent with the evidence of prior studies (Del Guercio and Tkac 2002; Xiao et al. 2014; Pástor et al. 2015) that investor decisions on mutual funds are affected by fund age, as downward spirals in general market returns pose a threat to the value of investor assets. Stafylas and Andrikopoulous (2019) analyzed the determinants of fund performance under different market conditions using a Markov regime switching framework. Their results, however, suggest that the predictive power of fund age over performance is more evident in the bullish state of the market than in the bearish state. They document that recently established funds generally exhibit superior performance in periods of low volatility relative to their older competitors in the industry, while a reverse of this state of performance holds for old and young funds during periods of high market volatility. Comparing the results for *LNAGE* of funds in the cross-section with the results of *FLOW* and *LTNA* in Table 2, it can be observed that most of the funds with significant coefficients for *LNAGE* in the bearish state also report significant coefficients for *FLOW* and *LNTNA* in the bearish state. This relationship is linked to the expected behavior of investors to be influenced by fund age and size when finalizing investment decisions on mutual funds.

Stafylas and Andrikopoulous (2019) verified that small and young funds are able to generate superior returns relative to old and large funds, even in bearish states of the market, and hence justifies investors' favorable decisions on them under changing market conditions. The significance of coefficients of *STDFND* for funds in the cross-section is larger in the bearish state (22 significant coefficients; with most of them being negative) than in the bullish state (15 significant coefficients), which indicates that fund risk exerts a more retrogressive impact on the performance during periods of market decline. Based on the results of Markov regime switching regressions, Huang (2012) attributed persistence in fund return variability to inferior market timing ability over the business cycle on the part of active managers. It can be observed from the results shown in Tables 2 and 3 that most of the funds with significant coefficients for *STDFND* also report significant coefficients for *FLOW* and *LNTNA*. This evidence explains that investors' cash allocation decisions on mutual funds are influenced by portfolio risk and funds' assets under management (Sirri and Tufano 1998; Guercio and Reuter 2014).

When fund contributors' decisions on funds are largely driven by their attitude toward fund risk and the size of funds, they tend to allocate funds disproportionately across fund managers, which ultimately affects the direction of fund performance. The behavior of investors in this context can be explained by the AMH as a way of adapting to changing market conditions due risk aversion and disposition effects. The cross-sectional average coefficient of *STDMKT* in the bullish state (S1) is −2.563 (13 significant coefficients). On the other hand, the coefficient average of *STDMKT* in the bearish state (S2) for the funds cross-section is −0.876 (21 significant coefficient). These show that the level of market return dispersions significantly influences the direction of fund performance more in the bearish regime than in the bullish regime of the market. However, in an analysis of fund performance determinants with Markov switching models, Badea et al. (2019) found that the effect of market risk on fund performance is generally minimal in unchanging market conditions, although they found evidence of a link between the direction of general market returns and individual fund performance.

In general, the cross-sectional analysis shows that fund age, fund risk, and market risk exert varying and more significant impacts on fund performance as compared to other significant variables across different funds under changing market conditions. These three variables (fund age, fund risk, and market risk) represent the set of fund-level and systemic determinants of cross-sectional differences in mutual fund performance under time-varying conditions of the market in South Africa. These results imply that exogenous factors drive fluctuations in the interactions between mutual fund flow and performance under time-varying market conditions in South Africa, and affirms the normative guidelines of the adaptive markets hypothesis as explained by Apau et al. (2021) and Kunjal et al. (2017).

4.4. Smoothed Regime Probabilities

Figures 1 and 2 plot the smoothed probability of regime 1, the bullish state, P[St = 1], fitted to the 33 funds' performances for the regime switching model specified in Equation 16. The values of the smoothed probability series are typically very close to either zero (regime 2, bearish state) or one (regime 1, bullish) and the smoothed probability series do not frequently switch between the bullish state and the bearish state. The smoothed probability is of interest in economically interpreting the regime switching behavior of the performance of funds and when they occur. From Figure 1, it can be observed that most funds experienced significant volatilities and declines in performance during the period of global financial meltdown, as funds' performance generally entered a bearish state (regime 2) for a specified period of time.

The performance of funds generally recovered from the bearish state at the beginning of 2009, when they entered a bullish state (regime 1). The presence of bullish performance across funds around 2017/2018 can be explained as flow-driven performance and not as a result of superior trading expertise of fund managers, as investors' cash allocations to funds increased significantly during this period (Rangongo 2018). This represents a dynamic form of adaptation to changing market conditions by way of wind fall returns on the part of fund managers, which can be explained by the AMH. In general, the performance funds in the sample are highly volatile under changing market conditions. This evidence is closely linked with the position of the extant literature. Turtle and Zhang (2012) employed Markov switching regressions to analyze the time-varying performance of mutual funds. Their evidence suggests that the risk-adjusted performance of mutual funds varies with the dynamics of markets that are dominated by international investments, as they are susceptible to the effects of international market fluctuations. They explained that emerging market funds (South Africa included) exhibit superior performance when the global financial outlook assumes a positive trend relative to returns on investments, implying a significant dependence on foreign inflows. Foreign exchange volatility was identified as a significant determinant of emerging markets funds' performance. Scholars have explained that during the period of the financial crisis, the level of risk increased, and funds experienced high levels of outflow that caused higher volatility (Ben-David et al. 2012; Manconi et al. 2012). Furthermore, the increased volatility in fund performance of South African funds is linked to capital reallocation from emerging markets to advanced markets during the financial crisis in furtherance with the flight-to-safety hypothesis (Fratzscher 2012). Overall, the inconsistent flow-performance patterns among sampled funds makes it difficult to draw any other conclusion about the performance of mutual funds in South Africa compared to explaining that the dynamics of their performance lack stability. This corresponds with the estimated average regime transition probabilities and the expected durations presented in Tables 3 and 4, which shows that a significant percentage of the transition period is spent in the volatile (bearish) condition of the market.

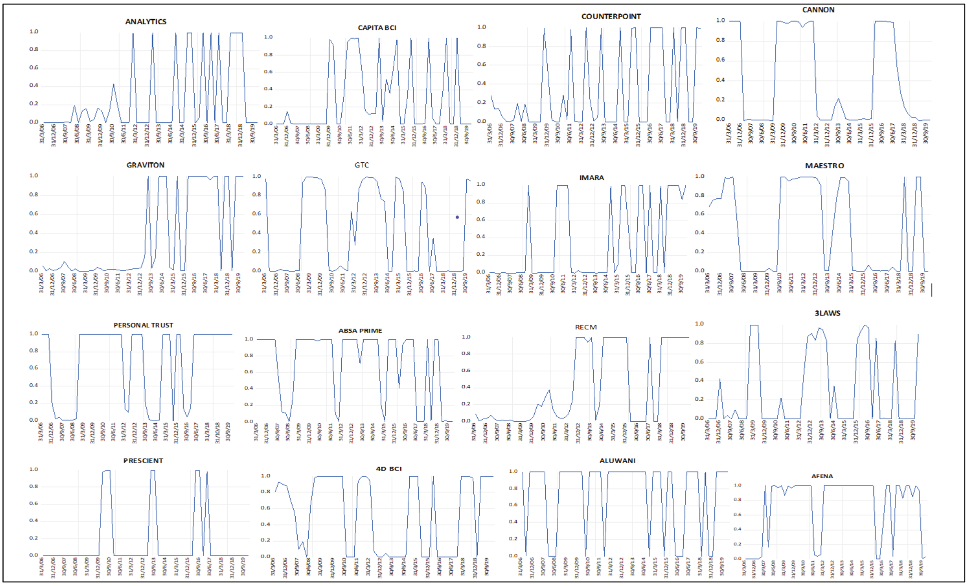

Figure 1. Smoothed probability of regime 1 (bullish state) for the Markov switching model.

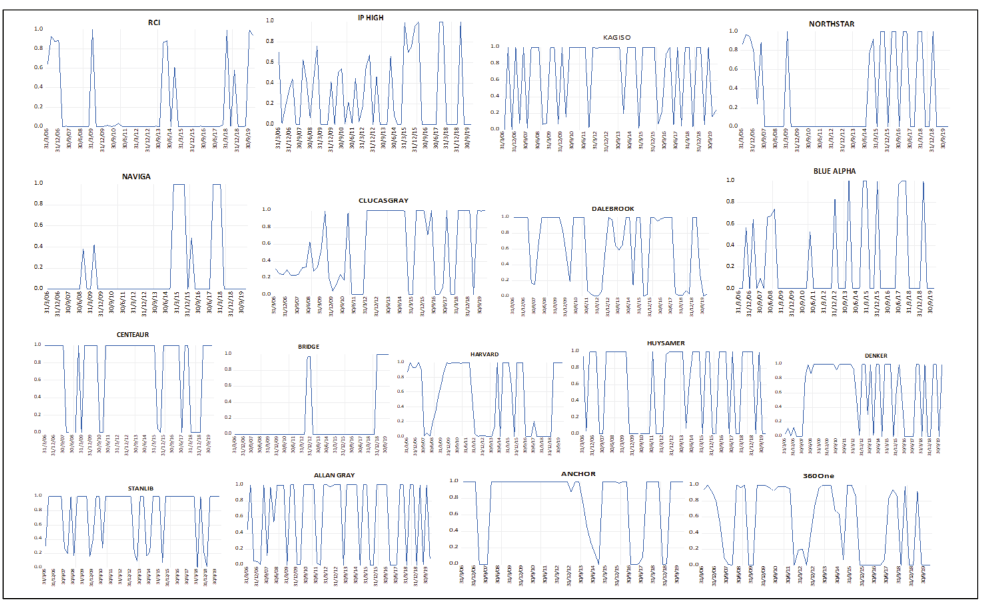

Figure 2. Smoothed probability of regime 1 (bullish state) for the Markov switching model.

Table 4. Regime transition probabilities.

	Regime 1	Regime 2
Regime 1	0.659	0.340
Regime 2	0.314	0.669

Source: Authors' estimations (2021).

4.5. Regime State Analysis

Regime transition probabilities and expected durations in bullish and bearish conditions are reported in Tables 4 and 5, respectively. Table 4 reports the average transition probabilities between different regimes of the system for the sampled funds. From the table, the average probability of staying in the bullish state (regime 1) is 0.659 while the probability of regime 1 transitioning to regime 2 (bearish state) is 0.340. The probability of staying in the bearish regime (regime 2) is 0.669 and the probability of regime 2 transitioning to regime 1 is 0.314. These results suggest that regime 2 has the highest continuous probability, and hence, is the most stable regime.

Table 5. Expected durations.

	Probability	Duration
Regime 1	0.491	4.43
Regime 2	0.509	4.59

Source: Authors' estimations (2021).

Table 5 reports the average expected duration of regime transitions of the estimated MS model. From the table, regime 1, which denotes the bullish condition, is expected to persist for an average of 4.43 quarters while regime 2, denoting the bearish condition, is expected to persist for 4.59 quarters on average, which represents 49.1% and 50.9% of the sample period, respectively. Regime 2 (which is the bearish condition) is the most persistent regime as it accounts for 50.9% of the constant expected duration for the sample period.

5. Conclusions

The purpose of this study was to conduct a non-linear analysis of the determinants of mutual fund performance within a regime switching framework to elicit explanations for the inconsistent flow–performance dynamics in South Africa. As a result, the Markov switching model was employed as a suitable analytical tool to test the effect of fund performance determinants across bullish and bearish conditions of the market. The main findings of the study are presented. First, the predictive power of fund flow over performance is more pronounced in the bearish state of the market than in the bullish state, which is indicative of high investor sensitivity to fund performance in lower periods of the market than in upper periods. Second, similar to the effect of fund flow, other fund-specific variables, namely fund-level fund risk, fund size, and fund age, exert strong deterministic influences on fund performance during market downturns compared to upturns. This finding is linked to the flight-to-liquidity assets and risk-aversion behavior of fund contributors during volatile conditions of the market. Lastly, the study found that the predictive effects of market risk and economic size on fund performance are more evident in bearish market conditions than in bullish conditions. This evidence affirms that the direction of macroeconomic growth and market volatility levels are significant determinants of fund performance. This study contributes to the literature on mutual funds by providing novel perspectives on the effect of fund-specific and systemic factors on fund performance under a regime switching framework in the South African context.

The findings of the study have significant policy implications for fund contributors, fund managers, and economic management frameworks. First, younger funds should remain strategic in their trading activities, as the advantage in fast-paced growth could lead to deteriorations in long-term performance when administrative expenses become excessive as a result of overtrading. In addition, fund managers should remain strategic in market timing to optimize stock-picking choices as increased market volatility affects fund performance. Above all, policymakers should implement policies that create a conducive economic environment as the direction of economic growth and market volatility are linked with fund performance.

This study has recognizable limitations in terms of the variable characteristics and the frequency of data employed in the analysis due to data availability issues. The study mainly focused on measurable fund-level and systemic variables and used quarterly data. Future studies should include variables that capture managerial and investor sentiments as time-varying investor behavior may affect fund performance. Additionally, the use of high-frequency data allows for more data points to enhance the Markov switching analysis.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/economies9040161/s1, Table S1: Normality and unit root test on the MS variables.

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economies

Article

The Influence of Global Financial Liquidity on the Indonesian Economy: Dynamic Analysis with Threshold VAR

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Abstract: Empirical studies of the global liquidity spillover on Indonesia's economy are still relatively limited. Most of the global contagion literature on Indonesia's economy focuses only on the effects of real shock (on output) due to financial shock. We assert that the effect of global output on Indonesia macroeconomic conditions is a fairly relevant issue to be studied. This research aims to investigate the interdependent relationships between world GDP, world commodity prices, world inflation, trade flows, capital inflow, capital account transactions, reserve accumulation, global liquidity (e.g., global broad money), and monetary aggregates, with regard to Indonesia's GDP variables and inflation. This paper uses threshold vector autoregression (TVAR) to capture regime changes in the variables of the world economy. World economic data and Indonesia's economic data were utilized to prove different responses to the world economic situation in two different regimes. This research identified two groups of upper regime and lower regime world variables—namely, world inflation, world GDP, and world commodity prices. TVAR estimation resulted in a smaller residual sum of squares compared to VAR estimation. Different regimes resulted in differences in Indonesia's economic responses due to the shock of world economic variables. The findings generated by this research are expected to be insightful to monetary policymakers in Indonesia.

Keywords: threshold VAR; global inflation; inflation; financial global; finance liquidity; exchange rate; commodity

JEL Classification: E31; E32; C33; E60; E42; F32

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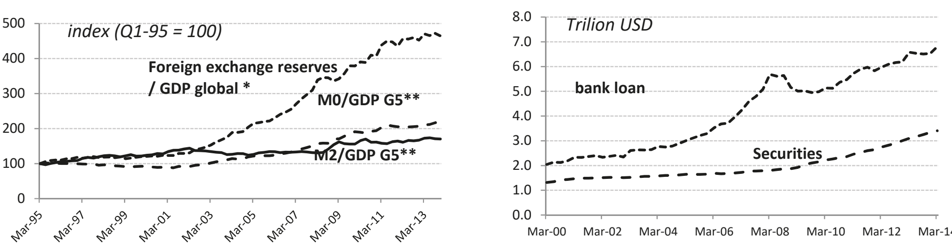
1. Introduction

For more than two decades after the Cold War, the world economy was increasingly integrated, in terms of both trade—through various free trade agreements—and financial aspects. Aizenman et al. (2008) found that the level of financial openness in both developed and emerging countries in Asia and Latin America tended to increase over the period of 1991–2006, along with the lax rules of international exchange flows and international capital flows. The activities of multinational corporations and financial innovations—such as corporate bond issuance and stock listing abroad—also further complicate the inter-state financial linkages in the present (Azis and Shin 2013). These global monetary and financial conditions are generally summarized under the umbrella term "global liquidity", which refers to the availability of funding in global financial markets. Even so, in popular discourse, the term global liquidity is often used for more specific matters, such as monetary policy in developed countries or inter-state capital flows, which are more accurately considered to be a subset of the global liquidity issues (Domanski et al. 2011).

Other aspects of the global economy that often become concerns are global production, global inflation, and global commodity prices. These three variables play a notable role in the economic development of developing countries. For developing countries, economic development is measured by several variables, including GDP, inflation, trade flow, capital inflow, capital account transactions, and foreign exchange, among others (Aizenman et al. 2008). As identified by Azis and Shin (2013), the first surge period (1995Q4–1998Q2) culminated in the Asian financial crisis, while the second surge (2006Q4–2008Q2) was closely related to the credit boom that created preconditions for the global financial crisis. The current global economy may be in a third surge, fueled by a highly accommodative monetary policy in the wake of global recession, along with high commodity prices.

The roles of several variables—such as GDP, inflation, trade flow, capital inflow, capital account transactions, and foreign exchange—affect the influence of global variables on GDP and inflation in developing countries. For most countries, foreign exchange accumulation is a logical response to a possible reversal of capital flows at all times, and to reduce the adverse impacts of economic openness on exchange rate movements (Aizenman et al. 2008). However, the accumulation of foreign exchange may erode global financial stability by having the bulk of financial instruments invested in developed countries, thereby improving only these countries' financial conditions (Domanski et al. 2011; Landau 2013).

As one of the emerging Asian countries, Indonesia did not escape the phenomenon of this financial integration. Indonesia's capital inflows have shown an upward trend relative to GDP and inflation since the end of the Asian crisis. The percentage of Indonesian financial assets held by foreigners has also shown an upward trend over the past eight years (Figure 1a; "*" indicates the total loan from the US, European Union, and Japan, while "**" represents finance from the US, European Union, Japan, UK, and Canada). The fluctuations now tend to be more extreme (Figure 1b). In line with this, the awareness of economic actors and takeover policies in Indonesia is increasing about the vulnerability of domestic economic conditions to fluctuations in global liquidity.



(**a**) (**b**)

Figure 1. Foreign exchange, monetary aggregates, and loans. (**a**) Total loan for several countries. (**b**) Foreign exchange reserves and monetary aggregates. Source: IFS, BIS.

Empirical studies of the global liquidity spillover on Indonesia's economy are still relatively limited. Most of the global contagion literature on Indonesia's economy (Pratomo 2013) focuses only on the effects of real shock (on output) due to financial shock; in contrast, fluctuations in financial indicators often precede and predict changes in Indonesia's GDP (Ng 2011). Several other studies have examined the impact of global liquidity on Indonesia in more specific contexts, such as the work of Yiu and Sahminan (2015), who studied the relationship between capital inflow and property prices. Based on these considerations, we believe that global output's effect on Indonesia's macroeconomic conditions is a reasonably relevant issue to be studied.

Matsumoto's study (2011) provides a helpful framework for studying the impacts of worldwide production—particularly in Indonesia, where such research remains restricted. The main aim of this research is to identify the interdependent relationships between world GDP, world commodity prices, world inflation, with regard to Indonesia's GDP variables and inflation. These relationships can consist of dynamic, direct, and indirect relationships. The appropriate analytical model for analyzing this relationship is vector autoregression (VAR). The VAR method used in this research allows us to detect the heterogeneity of

Indonesia's output, as well as inflation, in response to the shock of certain global variables. This statement is crucial, considering that several other studies (Sousa and Zaghini 2007) concluded that the impacts of global factors on economic circumstances in different nations might vary significantly. These variations can be linked to variations in each country's financial systems. The standard VAR model was developed into a threshold VAR model because of the nonlinearity of response variables at various levels.

This paper describes different responses to certain situation variables, whereas other studies assume that the variables respond the same way in all situations. In reality, for different world GDP regimes, the economies of small countries will respond with different magnitudes. This study determines the appropriate threshold values for several global variables that separate the different regimes.

This study's contribution to the literature is the provision of a research perspective wherein the response or impact of exogenous variables on endogenous variables may vary. This study suggests an idea of the existence of a threshold value as a limit for the occurrence of differences in responses to the global financial liquidity regime. Afonso et al. (2018) used a threshold VAR analysis to study the linkages between changes in the debt ratio, economic activity, and financial stress within different financial regimes. Chowdhury and Ham (2009) used TVAR because they assumed that low-to-moderate inflation is favorably related to economic growth in some developing countries. After a certain threshold, the level of inflation will undermine growth. Romyen et al. (2019) used the threshold gross domestic product (GDP) because, at high GDP, the impact of exports on GDP will be higher than at low GDP.

After this introduction, there will be a discussion of the theoretical background, followed by a review of the relevant literature. There then follows a description of the methodology, and the data and results are analyzed. Finally, there are several conclusions. The Indonesian economy will respond in different ways to the changing world economy. The disclosure of the threshold of world economic variables implies that the world economy being above the threshold will cause the Indonesian economy to be different if it is below its threshold value. A significant threshold value indicates that the nonlinear model is better than the linear model. The nonlinear model is better for identifying Indonesia's economic response at the level of the world economy, which often fluctuates.

2. Theoretical Background

The main theory of this paper is based on the monetary modeling of Christiano and Eichenbaum (1992). Greater liquidity lowers the nominal interest rate in the short term (liquidity impact) and, hence, decreases loan costs and boosts asset prices as the discount rate decreases. Additionally, if prices and wages suffer temporary nominal rigidity, liquidity expansion will also increase inflation expectations, suppressing the expected inflationary interest rate. This expansion of liquidity also encourages risk-taking behavior in the banking sector, and the financial markets in general (Adrian and Shin 2008).

Mundell and Fleming modeled the balance in the money market (LM), goods market (IS), and foreign exchange market (BOP) in an open economy (Frenkel and Razin 1987; Scarth 2014):

$$Y_t = DA_t(r_t) + NetX_t(ER, Y_t, Y_t^*) \tag{1}$$

$$Md_t(r_t, Y_t) = Ms_t(FER_t)/P \tag{2}$$

$$\Delta FER_t = NetX_t(s_t, Y_t, Y_t^*) + K_t(ir_t - ir_t^*) \tag{3}$$

where Y_t is GDP, K_t is the capital net inflow, DA_t is the domestic absorption, $NetX_t$ is the net export, FER_t is the foreign exchange reserve, Md_t is the money demand, Ms_t is the money supply, ir_t^* is the external interest rate, Y_t^* is world GDP, P is the price level, ir_t is the domestic interest rate, and ER_t is the nominal exchange rate.

The impacts of capital flow on the significant national factors (output, inflation, and inventory prices) investigated in this research depend on the exchange rate regime. In the fixed exchange rate regime, balance in Equation (3) on the foreign exchange market is accomplished by providing cash to the recipient of the capital flows.

Figure 2a explain the fixed exchange rate regime. If the global interest rate decrease under the domestic rate ir^*_{t+1}, capital inflow occurs to take advantage of this opportunity. This would appreciate home currency. Central Bank sell of its foreign currency reserves to offset this capital inflow. Domestic interest rates have adapted to global interest rates at the new equilibrium point in this system. The decrease of the money supply would shifts the LM curve to the right until the domestic interest rate equal with global interest rate ir^*_t. Figure 2b explain the floating exchange rate regime. Conversely, if currency appreciation determines the exchange rate, it has a tendency to decrease the competitiveness of export products. The decrease of the global interest rate ir^*_{t+1} will cause downward pressure on the local interest rate. The pressure will move as the domestic rate closes to the global rate. When negative differential occurs ($ir^*_{t+1} - ir^*_t < 0$), the central bank holds no monetary expansion. When LM Curve holds constant, capital will flow in of the domestic economy. This appreciation the domestic currency will decrease the net export. Decreasing net export shifts the IS to the left until the domestic interest rate equal to the global rate ($ir_t = ir^*_t$).

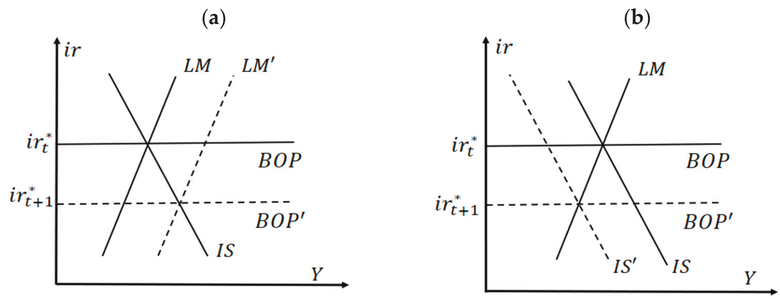


Figure 2. Expansionary shock and global liquidity in the Mundell–Fleming model. (**a**) Fixed Exchange Rate. (**b**) Floating Exchange Rate.

In this case, liquidity in the global safe asset market is identified by the monetary aggregate m^*_t, whereas liquidity in the global risk asset market is projected by the risk premium rp_t. The global economy is modeled according to the following equations:

$$Y^*_t = E_t Y^*_{t+1} - \frac{1}{\rho}\left(ir^*_t - E_t \Delta P^*_{t+1}\right) \tag{4}$$

$$\varepsilon(M^*_t - P^*_t) = -\frac{\beta}{1-\beta} ir^*_t + \rho Y^*_t \tag{5}$$

$$\Delta P^*_t = \beta E_t \Delta P^*_{t+1} + \rho\kappa Y^*_t \tag{6}$$

where P^*_t is the global price level, Y^*_t is the global GDP, and ir^*_t is the global interest rate. Equation (5) describes equilibrium in the money market (LM), Equation (4) in this case describes equilibrium in the goods market (IS), while Equation (6) is a reflection of the tradeoff between output and inflation (Phillips curve). Exogenous shocks affect liquidity in the global safe asset market, where M^*_t increases permanently. The output and rate of domestic inflation for a small open economy are modeled as a function of past values, current values, and expectations of future value of global GDP (Y^*), nominal exchange rate (ER), real exchange rate (Q), global inflation (ΔP^*), and domestic interest rate (ir), as follows:

$$Y = f(Q, Y^*, \Delta P, ir) \text{ Where } \frac{\partial Y}{\partial Q} > 0;\ \frac{\partial Y}{\partial Y^*} > 0;\ \frac{\partial Y}{\partial(\Delta P)} > 0;\ \frac{\partial Y}{\partial ir} < 0 \tag{7}$$

$$\Delta P = f(\Delta S, \Delta P^{*}, \Delta Y) \text{ Where } \frac{\partial(\Delta P)}{\partial(\Delta \mathrm{E})} > 0;\ \frac{\partial(\Delta P)}{\partial(\Delta P^{*})} > 0;\ \frac{\partial(\Delta P)}{\partial(\Delta Y)} > 0 \tag{8}$$

The ER is assumed to move in accordance with the uncovered interest rate parity, i.e.,:

$$E_t \Delta ER_{t+1} = ir_t - ir_t^{*} + rp_t \tag{9}$$

The solution to this domestic model is determined by the rate function ir_t. In this case, one assumes that the central bank has a degree of monetary independence γ. Thus, interest rate movements will partially follow the domestic targets, which follow the Taylor rule:

$$ir_t = \gamma\left[\bar{i} + \phi\left(Y_t - \overline{Y}\right) + \varphi\left(\Delta P_t - \overline{\Delta P}\right)\right] + (1-\gamma) ir_t^{*} \tag{10}$$

Equation (10) assumes that domestic monetary policy plays a significant role in determining the spillover effect of global liquidity. $0 < \gamma < 1$ implies that liquidity expansion in the global safe asset market will have a positive effect on inflation, GDP, and domestic asset prices. The appreciation of the exchange rate can offset a rise in inflation, up to a point. The decrease in rp_t and expansion of liquidity in the global risk asset market will have a spillover effect in a similar direction.

The theoretical description of the relationship between variables in the TVAR model is explained as follows: Equation (7) explains the impact of global GDP (Y^{*}), real exchange rate (Q), domestic inflation (ΔP), global inflation (ΔP^{*}), and domestic interest rate (ir) on domestic GDP (Y). Equation (8) explains the impact of nominal exchange rate (ER) and global inflation (ΔP^{*}) on domestic inflation (ΔP). Equation (5) explains the role of the global price level in determining the level of global liquidity. Equations (4) and (6) explain the dynamic relationship between global inflation (ΔP^{*}) and global GDP (Y^{*}).

Equation above show that global GDP (Y^{*}), domestic GDP (Y), global inflation (ΔP^{*}), and domestic inflation (ΔP) dynamically influence one another. The world commodity price P^* is included because it plays an important role in determining world exchange rates and inflation. Endogenous and dynamic interrelationships were applied through the VAR model. If the VAR model assumes the impact of the invariant variable, TVAR assumes the impact between the variant variables, depending on the global economic regime.

Literature Review

Brana et al. (2012) discovered the structural breaks in this excess liquidity growth in 1995, wherein subsequent periods showed a higher and more persistent rate of growth. Monetary aggregate growth has been decoupled from global output growth, leading to what is known as excess liquidity.

Previous studies (Brana et al. 2012; Belke et al. 2010a; Sousa and Zaghini 2007) showed that global liquidity positively influenced short-term output. Psalida and Sun (2011) also observed positive effects on the credit gap, indicating the role of credit channels in the transmission of global liquidity impacts. Meanwhile, Matsumoto (2011) found that the rising levels of global risk aversion, as measured by the CBOE volatility index (VOX index), have a negative effect on output in various developed and emerging countries. Research conducted by Sousa and Zaghini (2007) and Belke et al. (2010b) found that global liquidity expansion boosted inflation both at the global level and at the level of individual countries/groups of countries. This is also consistent with the findings of Ciccarelli and Mojon (2010) that there is a robust error-correction mechanism between domestic inflation and global inflation.

3. Methodology

Estimation Methods

According to Galih and Safuan (2018), there is a simultaneous and dynamic two-way relationship between inflation and economic growth. This relationship experiences a regime change, to be positive or negative, which is suspected to occur based on certain factors within a country. These factors vary between economies because each country has unequal economic characteristics, e.g., policy, ideological, geographic, etc. Therefore, additional variables are needed in order to capture the relationship between inflation and economic growth. In our opinion, it is important to capture the differences between these characteristics.

We compiled a threshold vector autoregression (TVAR) model involving liquidity indicators in the global market, indicators of Indonesian macroeconomic and financial variables (or peers), and other global variables as controls. TVAR is an appropriate method of identifying the nonlinear effects of exogenous shock on a system of mutually endogenous variables, and is therefore widely used in empirical studies of macroeconomics in general, and of global liquidity in particular. A complete description of the TVAR model is given in the work of Ekananda (2017) for the research of the interaction of banking variables using TVAR. Briefly, the TVAR framework is described as follows: a system of structural equations beginning with Equation (11), where Y_t is a vector of n endogenous variables, $B(L)$ is the matrix $n\ X\ n$ lag operator for Y_t, and e_t is error terms:

$$\Gamma Y_t = B(L)Y_t + e_t \tag{11}$$

The reduced form (Equation (12)) is obtained by multiplying Equation (11) by the inverse of Γ, which is the parameter of the contemporary relation for Y_t,. Equation (11) is changed in order to obtain the endogenous variable equation entirely on the left-hand side and the endogenous variable entirely on the right-hand side.

$$Y_t = \Gamma^{-1}B(L)Y_t + \Gamma^{-1}e_t$$

$$Y_t = B^*(L)Y_t + u_t \tag{12}$$

This system of Equation (12) can be expressed in terms of a moving-average vector:

$$(I - B^*(L))Y_t = u_t$$

$$Y_t = \Psi u_t \tag{13}$$

where $\Psi = (I - B^*(L))^{-1}$. The matrix Ψ is the impulse response function (IRF) of the reduced-form model, but the reduced-form u_t error term, in this case, is not economically meaningful. To identify the IRF against structural error or innovation t, the PVAR method applies two types of restriction to solve Equation (14):

$$\Gamma^{-1}e_t = u_t \tag{14}$$

The first restriction is based on the assumption that structural innovation is orthogonal, or uncorrelated between variables. This allows the normalization of the variance–covariance matrix Σ_e into an identity matrix, giving the following equation:

$$\Gamma^{-1}\Sigma_e\Gamma^{-1'} = \Sigma_u \tag{15}$$

In this case, we applied Cholesky decomposition, which makes Γ^{-1} an orthogonal matrix, since this form of restriction guarantees the fulfillment of the rank condition regardless of the exogeneity block restriction that we apply to the lag terms (Rubio-Ramirez et al. 2010). An appropriate variable is a crucial factor in ensuring the inference validity of this estimate. The TVAR model is a threshold model developed by Tong (1983), which is used to capture nonlinear phenomena in multivariate time series. The linear VAR model captures only linear impacts for all levels of data. The economy always makes adjustments at a certain economic level. The TVAR model calculates the threshold value of the economic variable used as an exogenous component. The TVAR model produces an efficient regression because its parameters are more flexible according to the variable threshold level. The hope is that TVAR regression results have a smaller residual sum of squares value.

Different thresholds can be implemented in the model. This research used two regimes to demonstrate high- and low-regime situations, dividing the variables into two regimes so that the differences were easier to investigate. The reason for implementing a threshold is because changes in impact can be seen in certain economic situations. In simple regression, the impact of independent variables is considered fixed for various economic situations. We used a dummy variable to explain the effects of two distinct circumstances.

We use TVAR developed by Balke (2000). The TVAR model consists of the dependent variables lag and threshold, and can be shown as follows:

$$Y_t = D^1 + A^1 Y_t + B^1(L)Y_{t-1} + \left(D^2 + A^2 Y_t + B^2(L)Y_{t-1}\right) I_t[C_{t-d} > \gamma] e_t \quad (16)$$

where Y_t is the vector of the endogenous variable, and $I_t[C_{t-d} > \gamma]$ is an indicator function that has a value of 1 when the lag threshold C_t is lower than critical threshold γ, and 0 otherwise. The model identifies two separate regimes based on C_{t-d}, where d is the time lag relative to γ, which is endogenously determined by the system. If $I_t[C_{t-d} > \gamma]$ is 0, then the estimation result is $D^1 + A^1 + B^1(L)$, whereas if $I_t[C_{t-d} > \gamma]$ is 1, then the estimation becomes $D^1 + D^2 + A^1 + A^2 + B^1(L) + B^2(L)$. The existence of this asymmetry can be identified by the threshold vector constant term D, and the different matrix coefficients A and $B(L)$ in each regime.

In the analysis process, TVAR is different from the general VAR method. The difference between the two methods is the existence of a threshold variable. TVAR calculates nonlinear IRF (impulse response function), which captures variable responses to the shock in different regimes. Researchers formed the TVAR model through several testing stages—namely, stationary testing, stability testing, determination of optimal lag, and co-integration testing. Further analysis of the TVAR or VAR models includes IRF and FEVD analysis. Particularly for TVAR, threshold estimation and nonlinear IRF analysis were performed to determine responses in terms of endogenous variables in the event of certain shock variables.

Due to its theoretical nature, the selection of variables and the proper determination of restriction are the most crucial factors in TVAR estimation. We list the variables in this research as follows:

$$\begin{bmatrix} \mathrm{gdp}_t^{w} & \mathrm{infl}_t^{w} & \mathrm{comm}_t^{w} & \mathrm{gdp}_t^{ind} & \mathrm{inf}_t^{ind} \end{bmatrix} \quad (17)$$

where gdp_t^{w} is the real world GDP, inf_t^{ind} is the consumer price level (Indonesian), infl_t^{w} is global inflation using the world GDP deflator, comm_t^{w} is the global commodity price level, and gdp_t^{ind} is the real GDP of Indonesia. This sequence is based on theories and literature on global shock transmission. The global variable block is placed before the domestic variable blocks in order to avoid the contemporary effects of domestic variables on global variables, in accordance with the assumption that shock in a small open economy such as Indonesia cannot affect global economic conditions.

The output is placed at the beginning, in accordance with the findings of Christiano et al. (1998) that output and inflation only react to liquidity shock after a certain lag. Inflation comes after output but before the liquidity/monetary and asset prices (commodities, stocks), according to the assumption of nominal rigidity in the Keynesian/neo-Keynesian model, where the price level adjusts only to shocks on other variables after a certain lag (Williamson and Wright 2010). Meanwhile, the prices of assets such as commodities, currencies (exchange rates), and stocks are placed most recently on their respective blocks, in accordance with the efficient market hypothesis, in which financial markets can react instantly to new information that may shape expectations of the asset price (Malkiel 2003). The following are the model specifications in this research, where the model country used was Indonesia. In this model, it is assumed that contemporaneous effects follow Cholesky's rules, wherein the order is based on Balke (2000). The general equation of TVAR is:

$$Y_t = (B_1 Y_t + B_2(L)Y_{t-1} + B_3(L)Y_{t-2}) I_t(C_{t-d} > \gamma) + u \quad (18)$$

The complete equation of TVAR is as follows:

$$\begin{bmatrix} gdp_t^w \\ infl_t^w \\ comm_t^w \\ gdp_t^{ind} \\ inf_t^{ind} \end{bmatrix} = \left(\begin{bmatrix} & & & & \\ a_1 & & & & \\ a_2 & a_3 & & & \\ a_4 & a_5 & a_6 & & \\ a_7 & a_8 & a_9 & a_{10} & \end{bmatrix} \begin{bmatrix} gdp_t^w \\ infl_t^w \\ comm_t^w \\ gdp_t^{ind} \\ inf_t^{ind} \end{bmatrix} + \sum_{l=1}^{p} \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} & b_{15} \\ b_{21} & b_{22} & b_{23} & b_{24} & b_{25} \\ b_{31} & b_{32} & b_{33} & b_{34} & b_{35} \\ b_{41} & b_{42} & b_{43} & b_{44} & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{bmatrix} \begin{bmatrix} gdp_{t-1}^w \\ infl_{t-1}^w \\ comm_{t-1}^w \\ gdp_{t-1}^{ind} \\ inf_{t-1}^{ind} \end{bmatrix} \right) I_t(C_{t-d} > \gamma) + u_t \tag{19}$$

where C_{t-d} is the lag threshold variable (-1); I_t is a function indicator that has a value of 1 if the lag of the threshold variable is lower compared to the critical value threshold γ, and 0 otherwise; $B_1(L)$, $B_2(L)$, and $B_3(L)$ are the lag polynomial matrices; and u_t is an error term. The structure of the orthogonal Cholesky matrix B_1 shows the contemporaneous parameter to the right of the equation. This research assumes that some variables have endogenous and dynamic relationships. This dynamic relationship experienced a regime change due to the nonlinear relationships that occur in the threshold C_t or lag (-1) variables at various points. The selection of threshold variables in the model refers to the work of Chowdhury and Ham (2009). The selected thresholds are the real-world output gdp_{t-1}^w, world commodity index $comm_{t-1}^w$, and world inflation inf_{t-1}^w. This variable plays an exogenous role, affecting the economy in Indonesia.

This model has two regimes due to the existence of the threshold, where the inflation rate is below the threshold limit; hence, the economic conditions are in the lower regime; when the inflation rate is above the threshold, this means that the economic condition is in the upper regime (Galih and Safuan 2018). The selection of threshold variables is based on the role of past inflation rates in determining the actual or current inflation targets at that time.

The nonlinear relationship refers to the behavior change of some variables over a period of time, caused by certain factors or economic conditions (Suryanto et al. 2020). These factors allegedly occur due to changes in aggregate supply and demand, changes in wage rates, changes in inflation expectations, monetary crisis, or new government policies and central bank policies. The relationship between inflation and economic growth that occurs in an economy can also be affected by other conditions.

4. Results and Discussion

The selected domestic variables in this research were real GDP (output), Indonesian inflation, and world inflation.

All of the data incorporated in this research were obtained from The Central Bureau of Statistics (BPS), Bloomberg LP, and International Financial Statistics (IFS) databases (Table 1), all of which employed logarithms except for interest rate, global GDP, and global GDP deflator. We applied the Census X12 procedure to the leveled information to minimize the seasonal impact of the information, and used a year-on-year differential for the first differential. This study uses quarterly data between 1996:Q1 to 2018:Q4.

Table 1. List of variables.

Variable	Sources	
Global real output (gdp_t^w)		
Global deflator GDP ($infl_t^w$)	IFS	Year-on-year %
Global commodity price index SandP* ($comm_t^w$)	Bloomberg	
Real output Indonesia (gdp_t^{ind})	BPS, IFS	Base year 2010
Consumer price index (CPI) inf_t^{ind}	IFS	Base year 2010

Table 2 explains the descriptive statistics covering mean, median, and maximum values, etc. To fundamentally determine the normality, as described by Brys et al. (2004), the ranges of skewness and kurtosis of these relevant data were within the range of −2.58

to +2.58, implying that the z-scores performed in a normal manner. The large Jarque–Bera values mean that the null hypothesis of normality was rejected at the 5% significance level, indicating that the gdp_t^w, $infl_t^w$, $comm_t^w$, gdp_t^{ind}, and inf_t^{ind} have a non-normal distribution. The gdp_t^w, $infl_t^w$, $comm_t^w$, gdp_t^{ind}, and inf_t^{ind} series fluctuate in accordance with the impact of global economic crises.

Table 2. Data description.

Variable	gdp_t^w	$infl_t^w$	$comm_t^w$	gdp_t^{ind}	inf_t^{ind}
Mean	0.033	0.073	0.048	0.042	0.097
Median	0.033	0.049	0.027	0.056	0.076
Maximum	0.058	0.213	0.490	0.102	0.579
Minimum	−0.019	0.010	−0.633	−0.202	−0.006
Std. Dev.	0.014	0.058	0.215	0.049	0.096
Skewness	−0.986	1.377	−0.668	−3.147	3.592
Kurtosis	5.323	3.433	4.016	13.765	16.604
Jarque–Bera	35.598	29.802	10.805	596.100	907.286
Probability	0.000	0.000	0.005	0.000	0.000
Observations	92	92	92	92	92

Table 3 shows that the majority of variables were incorporated in one order in this research (I (1)); some of them are covariance-stationary or trend-stationary at the national level (Ekananda 2016; Enders 2009). Especially for GDP and the global GDP deflator, the data obtained from IFS are a percentage of year-on-year growth, so root units at this level cannot be known. The hypothesis of a root unit is denied for global GDP growth, but cannot be denied for global GDP deflator growth.

Table 3. Unit root test.

Variable	1st Difference
Global real output, gdp_t^w	−3.571 ***
Global deflator GDP, $infl_t^w$	−1.672
Global commodity price index, $comm_t^w$	−4.016 ***
Real GDP, Indonesia, gdp_t^{ind}	−3.059 **
CPI, Indonesia, inf_t^{ind}	−3.415 **

Phillips and Perron test at *lag*:1, with intercept and without trend. Level of significance: ** 95%, *** 99%.

To test the null hypothesis of linearity against the alternative of nonlinearity (t = 1, 2), where t indicates the threshold value, we used a multivariate extension of the linearity test by Hansen (1999), Hansen (2000), and Balke (2000) to test the statistical significance of the variable that is determined as the threshold indicator. The likelihood ratio (LR) test is formulated as follows: $LR_{01} = T\left(ln\left(det\hat{\Sigma}_0\right) - ln\left(det\hat{\Sigma}_1\right)\right)$, where $\hat{\Sigma}_0$, which is the estimated covariance matrix for the model, is related to the null hypothesis, and $\hat{\Sigma}_1$ is the estimated covariance matrix for the alternative hypothesis. We apply one threshold compared to applying more than one threshold. The division of two regimes in Indonesia was carried out by Galih and Safuan (2018) for Indonesian data.

Table 4 summarizes the LR Test for linearity for 1. The null hypothesis is linearity. The LR test statistic shows that the null hypothesis is rejected for all tests. Therefore, gdp_t^w, $infl_t^w$, and $comm_t^w$ can be used as thresholds for the VAR 1 threshold.

Table 4. Likelihood ratio (LR) test.

LR Test for Linearity vs. One Threshold	gdp_t^w	$infl_t^w$	$comm_t^w$
LR statistic	204.66862	257.21503	245.84690
p-value	0.0000	0.0000	0.0000
Estimated threshold	0.03200	0.10500	0.02300
Observations	Upper: 86 Lower: 5	Upper: 17 Lower: 74	Upper: 88 Lower: 3

Tables 5 and 6 shows the SSR values of the VAR (no threshold) model and the TVAR model, where the TVAR SSR value is lower than that of the VAR model. The TVAR model estimates generate a lower and more efficient SSR. We used RATS programming software to solve TVAR models (Enders and Doan 2014). Table 5 shows the lower SSR values using threshold regression compared with linear regression. Threshold regression generates a more robust and effective estimate. This can be demonstrated by assessing the values of the non-threshold and threshold sum of squared residuals (SSR). Based on the Hannan–Quinn (HQIC) and Schwarz Bayesian (SBIC) information criteria, the VAR model with maximum lag of 1 (VAR (1)) is the most appropriate for the complete model without lag restriction, while the same criteria applied for each block separately lead to the VAR (1) or VAR (2) models.

Table 5. Comparison of SSR threshold regression compared to linear regression.

Equations	SSR for No Threshold	SSR for Threshold GDPW at 0.03200	
		Upper	Lower
GDP World (gdp_t^w)	0.0050132800	0.0038416049	3.69160×10^{-27}
Infl World ($infl_t^w$)	0.0186676242	0.0180228736	4.47940×10^{-27}
Comm World ($comm_t^w$)	1.6063031966	1.1363615102	5.28013×10^{-25}
GDP Indonesia (gdp_t^{ind})	0.0700752506	0.0696526329	1.01048×10^{-26}
Infl Indonesia (inf_t^{ind})	0.1649023310	0.1607237144	2.74020×10^{-27}
	Usable data: 91	Usable data: 86	Usable data: 5
		LR statistic: 204.66862 Degrees of freedom: 45	

Table 6. SSR of equations at threshold world inflation and threshold world commodity index.

Equations	SSR for Threshold World Inflation at 0.10500		SSR for Threshold Comm at 0.02300	
	Upper	Lower	Upper	Lower
GDP world (gdp_t^w)	0.0004696590	0.0028062174	0.0049166339	2.18237×10^{-26}
Infl world ($infl_t^w$)	0.0003151193	0.0173336004	0.0184403660	4.69865×10^{-27}
Comm world ($comm_t^w$)	0.1990931060	0.8375231994	1.5882522646	5.91141×10^{-26}
GDP Indonesia (gdp_t^{ind})	0.0247563092	0.0335070222	0.0699853918	7.08469×10^{-27}
Infl Indonesia (inf_t^{ind})	0.0420768776	0.0440724164	0.1607748630	6.62446×10^{-27}
	Usable data: 17	Usable data: 74	Usable data: 88	Usable data: 3
	LR statistic: 257.21503 Degrees of freedom: 45		LR statistic: 245.84690 Degrees of freedom: 45	

The study chose three threshold variables—namely, world GDP (gdp_t^w), world inflation ($infl_t^w$), and the world commodity index. World GDP rate (gdp_t^w) and world inflation rate ($infl_t^w$) play important roles in increasing Indonesia's GDP and inflation. Applying GDP as a threshold was the basis of the research of Romyen et al. (2019). In general, if the GDP regime is higher, the behavior of small countries' economic variables will be different if they are in a lower GDP regime. In conditions of higher world GDP, the response of Indonesian GDP is expected to be higher than in the event of lower world GDP. The use of world inflation and world price commodity index as thresholds is relevant to the research of Chowdhury and Ham (2009). In a high-world-GDP regime, the expectation is that Indonesian inflation will be high. In conditions of high world Inflation, the response of Indonesian GDP is expected to be higher than in the case of low world Inflation, due to the reaction of Indonesian production, which requires higher capital inflow and lower inflation. Likewise, Indonesian inflation will be high in the high-world-inflation regime, as a result of the response to capital outflows from Indonesia.

At a high world commodity index, the Indonesian economy will respond quickly by increasing commodity prices. At the low world commodity index, the Indonesian economy was slow to respond by lowering prices. Indonesia still needs imported raw materials for its production. Domestic prices must immediately follow the increase in world commodity indexes.

The second column shows SSR for the TVAR model with threshold GDPW. The model proposes a threshold GDPW value of 0.0320, which separates the VAR in the lower regime and upper regime. Upper and lower specifications are due to high and low statuses, and are more appropriate than crisis or non-crisis status. The crisis status must be relevant to the crisis status that the Indonesian monetary authority has issued.

The second column in Table 5 shows the SSR value of the TVAR model with inflation as the threshold. The world inflation threshold value is 0.1050. This value divides the inflation level into the upper regime and lower regime.

Column three in Table 6 shows the SSR value of the TVAR world commodity threshold index price; the threshold value is 0.023. This value divides the world commodity price index level into the upper regime and lower regime. Figure 3 shows the fluctuation data of the world inflation index and world commodity index. The division of inflation at the value of 0.105 is shown by the line that intersects the vertical scale of 0.105. The threshold occurred when the inflation index fell from 2002Q1 to 2018Q1. The inflation threshold divides the regime into two time-groups: before and after 2002Q1.

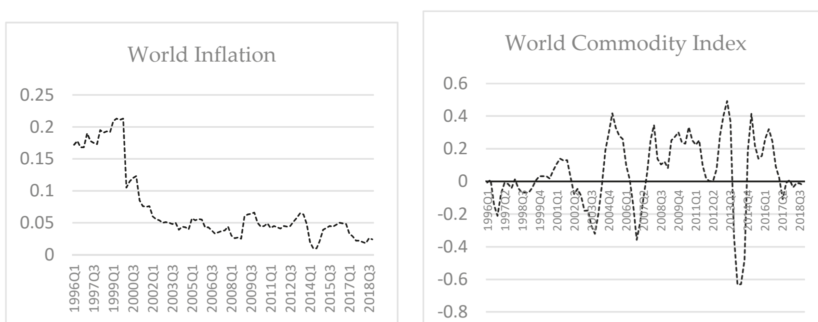


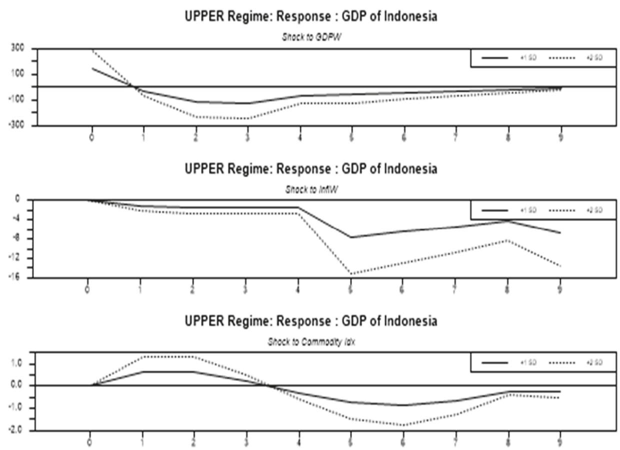
Figure 3. The fluctuation data of the world inflation and world commodity indices.

The division of the commodity index at 0.023 is shown at a value around zero (Figure 3, right panel). This value equally divides the commodity index into a regime of positive and negative indices. In general, the commodity index in the upper regime is positive.

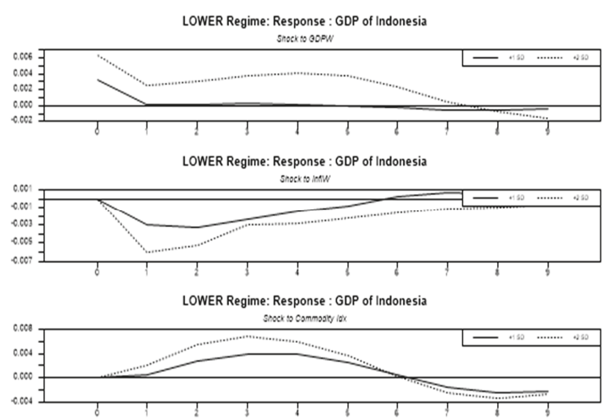
The IRF analysis of the TVAR model shows a different response if the same shock is applied to the variable shock propagator. The GDPW variable is significant as a threshold on the TVAR model's security system. The GDPW threshold value of 0.023 indicates that the world GDP growth is above 2.3%, causing the difference in the VAR estimation equation. The VAR equations in the two regimes shape the responses of GDP and inflation in Indonesia differently. As usual in VAR analysis, the impulse response function is still a good analytical tool to estimate the response in the future to a sudden change of the variable propagator. The following discussion concerns the response of Indonesian GDP variables (gdp_t^{ind}) and Indonesian inflation to shock from world GDP propagator variables (gdp_t^{w}), world inflation

(gdp_t^w), and the world commodity index ($infl_t^w$.). Response variables are divided into upper and lower regimes according to the world's GDP threshold (gdp_t^w), world inflation ($infl_t^w$), and world commodity index ($comm_t^w$). This study finds that Indonesia's GDP and inflation responses are higher in a high world GDP situation, as a result of the conducive influence of the world economy that drives the Indonesian economy forward.

Figure 4a shows the response of the Indonesian GDP (gdp_t^{ind}) to the shock of world GDP propagators (gdp_t^w), world inflation ($infl_t^w$), and the world commodity index ($comm_t^w$), sequentially. In accordance with Cholesky's orthogonalization, at high levels of world GDP, Indonesia's GDP responded positively to world GDP shock; positive responses declined for the next 10 quarters. Indonesia's GDP responded negatively to world inflation shocks; negative response continued until the 10th quarter. In the low regime, Indonesia's GDP did not respond to the shock of world commodities. Indonesia's GDP response caused by world GDP and world inflation was consistent with expectations (Galih and Safuan 2018).



(**a**)

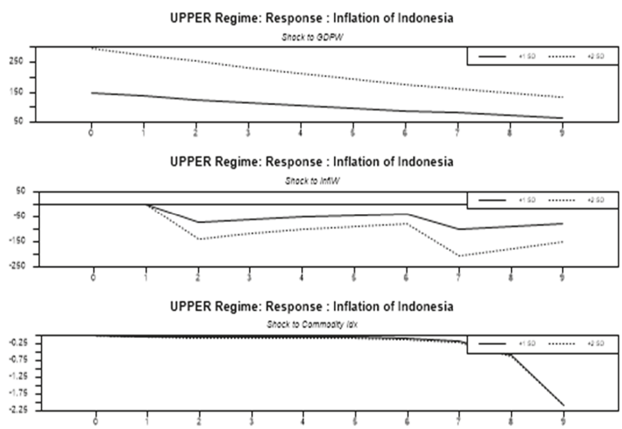


(**b**)

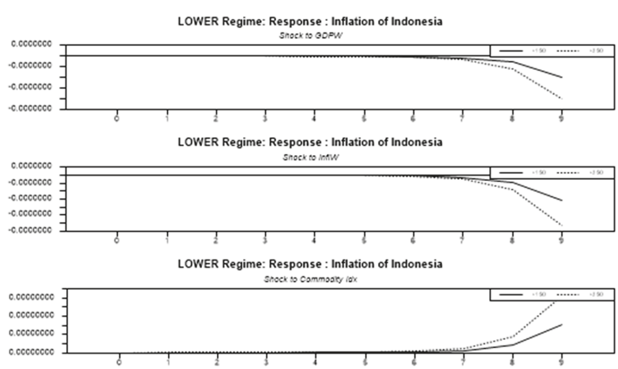
Figure 4. (**a**) The response of Indonesian GDP to the shock propagator in the upper regime; the threshold is world GDP. (**b**) The response of Indonesian GDP to the shock propagator in the lower regime; the threshold is world GDP. Note: Above the zero line responds positively. Below the zero line responds negatively.

Figure 4b shows Indonesia's GDP response to the same shock propagators in the low-world-GDP situation, where Indonesia's GDP does not respond to the shocks of world inflation, world commodities, and world GDP. In the case of shock propagators in all three variables, the low global economic situation cannot promote Indonesia's GDP.

Figure 5a shows the response of Indonesia's inflation $\mathrm{inf}_t^{\mathrm{ind}}$ to the same shock propagator. The study applied the same Cholesky's orthogonalization structure. The inflation response in the world's high-GDP regime differs from Indonesia's inflation response to the world's low-GDP regime. At high world GDP, Indonesia's inflation initially responded positively to the shock of world GDP; this response declined to its lowest in the third quarter. Similarly, Indonesia's inflation responded negatively to the shock of world inflation. In contrast to the shock of world commodities, world inflation responded positively in the 2nd and 3rd quarters. Indonesia's inflation response was stronger in the world's low-GDP regime. This fact indicates that at low GDP, Indonesia's inflation is more responsive than when the GDP regime is high. Some other authors have also explained this phenomenon (Gromb and Vayanos 2010).



(**a**)

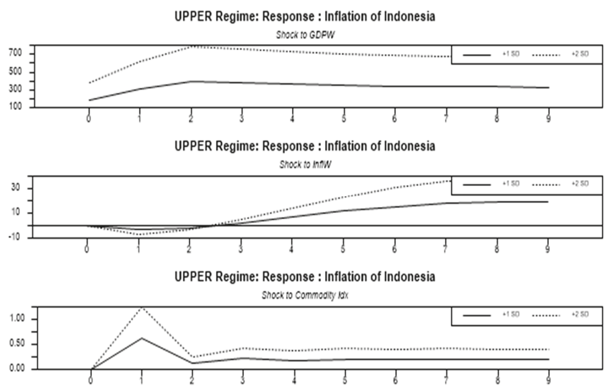


(**b**)

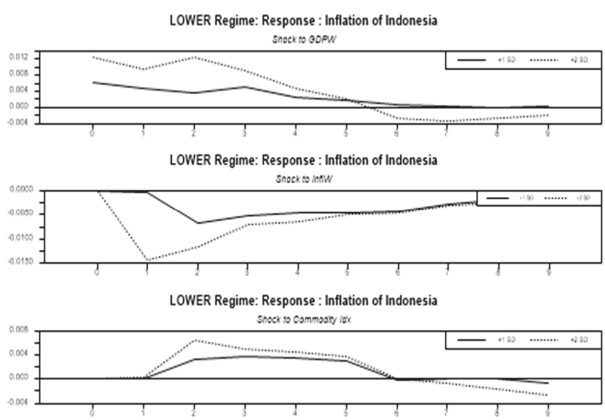
Figure 5. (**a**) The response of inflation in Indonesia to shock propagator in the upper regime; the threshold is world GDP. (**b**) The response of inflation in Indonesia to shock propagator in the lower regime; the threshold is world GDP. Note: Above the zero line responds positively. Below the zero line responds negatively.

Positive responses declined for the next 10 quarters. Indonesia's GDP responded to negative shocks in world inflation; the negative response continued until the 10th quarter. In the low regime, Indonesia's GDP did not respond to the shock of world commodities. Indonesia's GDP response caused by world GDP and world inflation was consistent with expectations (Giese and Tuxen 2007).

In this study, we analyzed the variable response to the world inflation situation ($infl_t^w$) as the threshold. Threshold world inflation is 0.105. Figure 3 shows inflation in the initial period of high research, and then after 1996Q1 the inflation index is low. The threshold divides the data into two parts according to a clear time period. The analysis in this paper is only aimed at inflation response due to shock propagators. In the upper regime period, during the period of high world inflation. Figure 6a on the left shows Indonesia's inflation will respond to the shock of global GDP positively. Inflation in Indonesia does not respond to shocks of world inflation. Indonesia's inflation did not respond to the shock of world commodities at the beginning of the period, but in Q1, Indonesia's inflation responded positively, but fell back until there was no response. This is because the inflation target applied in Indonesia is able to reduce the shocks of world inflation and world commodity prices.



(**a**)



(**b**)

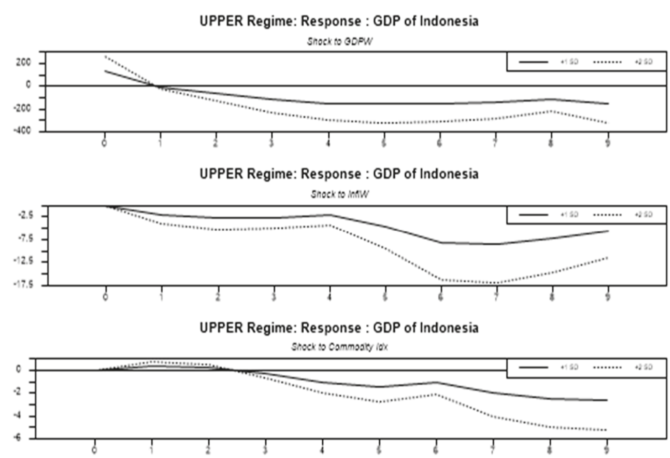
Figure 6. (**a**) The response of inflation in Indonesia to the shock propagator in the upper regime; the threshold is world inflation. (**b**) The response of inflation in Indonesia (inf_t^{ind}) to the shock propagator in the lower regime; the threshold is world inflation. Note: Above the zero line responds positively. Below the zero line responds negatively.

Figure 6b shows Indonesia's inflation response due to the shock propagators in the lower world inflation regime. The same phenomenon was observed as for the high regime, as described earlier. The magnitude of the response in the lower regime was greater. In the lower world inflation regime, inflation targeting policy is looser; thus, responses from various shock variables are more tolerated.

In the previous analysis, the threshold divides the world's GDP into two regimes, enabling further studying of the world commodity prices ($comm_t^W$) as the threshold. The world commodity index reflects changes in the prices of commodities traded in the world. Changes in commodity prices lead to world inflation and changes in the flow of funds between countries. The decline in oil prices was able to undermine the world's manufacturing industry and energy industry (Elizabeth et al. 2020). Increased commodity prices have not changed abruptly but, rather, through some adjustment processes following the global supply and demand mechanisms of commodities. Macroeconomic variables can capture the difference in response between the two regimes. The limit of change is reflected by the threshold value to be calculated in this study.

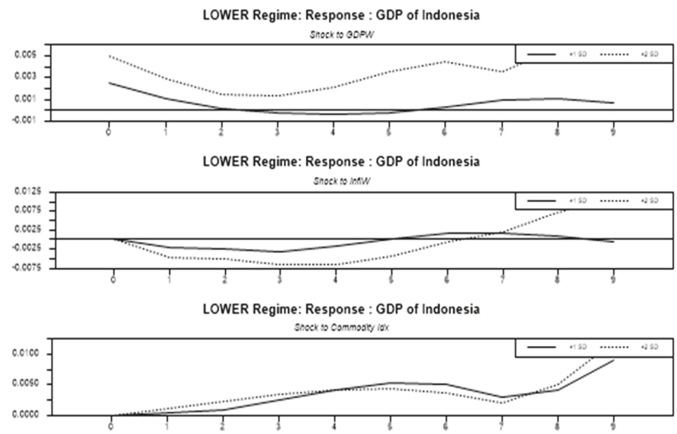
Threshold $comm_t^W$ is measured at 0.02300. Figure 3 shows the fluctuation of the world commodity index, which is divided into two equal parts; some are positive, and others are negative. Figure 7a shows the response of Indonesian GDP to shock propagators. We can conclude that the upper regime is indicated by a positive index increase. When there is an increase in the world commodity index, Indonesia's GDP experiences a bigger boost. This shows that Indonesia can increase its GDP when commodity prices in the world market increase. In the lower regime, the GDP response is weaker than in the upper regime.

The variable response in the lower regime shows different shapes. In general, the response variable in the lower regime is less responsive. The most obvious difference that occurred in Indonesia's commodity response was due to world commodity shock. Indonesia's commodity index responds positively to world shock commodities. This is consistent with the hypothesis that high world commodity prices will increase Indonesia's inflation.



(**a**)

Figure 7. *Cont.*



(**b**)

Figure 7. (**a**) The response of Indonesian GDP (gdp_t^{ind}) to the shock propagator in the upper regime; the threshold is world commodity price. (**b**) The response of Indonesian GDP (gdp_t^{ind}) to the shock propagator in the lower regime; the threshold is world commodity price. Note: Above the zero line responds positively. Below the zero line responds negatively.

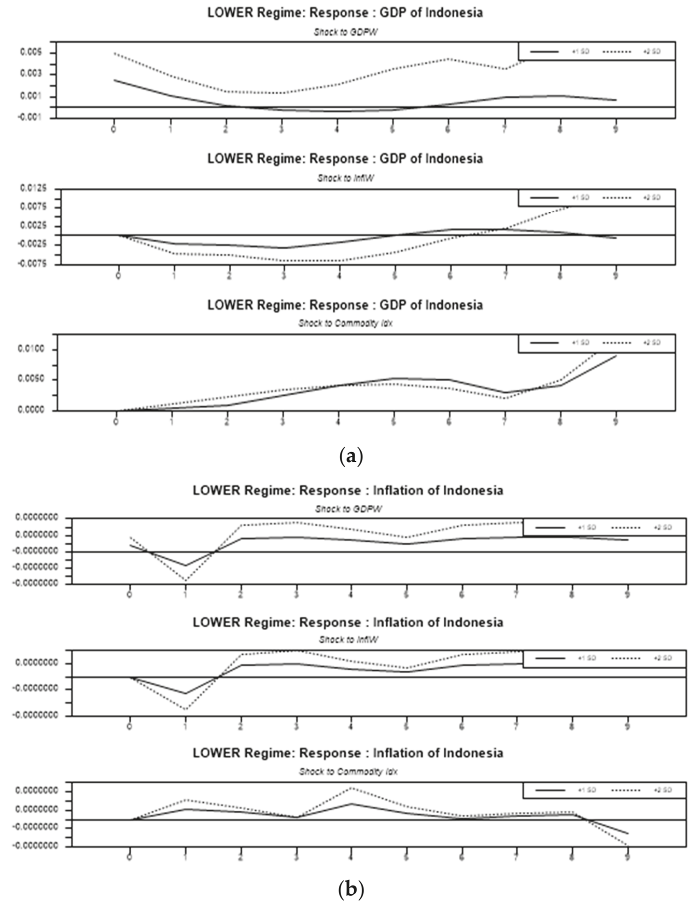
Figure 8 shows Indonesia's inflation response due to shock propagators. Inflation response in the upper regime is different compared to the lower regime. In the upper regime, Indonesia's inflation is positive at the beginning of world GDP shock (gdp_t^w). On the other hand, Indonesia's inflation does not respond to the shock of world inflation and world commodity prices. Figure 8a shows Indonesia's inflation responding negatively to the shocks of world GDP and world inflation.

This is consistent with the theory put forward by Domanski et al. (2011), who explained that when the world's commodity index is high, Indonesia's inflation will be pushed up. Indonesia implements inflation targeting to control domestic inflation so that inflation levels are maintained. The response to low world commodity index also shows low inflation, rising in Q1, but down again in the next quarter.

Table 7 summarizes the response of some variables to impulses under various regimes. The impulse response of TVAR function applies if other variables are not changed and interrupted. It is assumed that the IRF is valid for up to five periods to come before any other variables change. Brackets denote time (t). Responses recorded are due to the shock of two standard deviations (dashed line).

Description +/−(T1–T2): +/− shows a sign plus(+) or minus (−) of response direction. T1–T2 denote the start and end time, respectively. Sign: +,++,+++: denotes weak, moderate, strong respectively, in the positive direction. Sign: −,−−: denotes weak, moderate respectively, in the negative direction.

Based on the contents of Table 7, we can draw some conclusions: The impulse of world GDP causes an increase in Indonesia's GDP. Indonesia's GDP response is greater in the higher world GDP environment. Indonesia's inflation is driven to increase in the low- and high-world-GDP regimes. The impulse of Indonesia's inflation is driven to increase in the situations of both low and high world inflation.



(**a**) (**b**)

Figure 8. (**a**) The response of inflation in Indonesia ($\mathrm{infl}_t^{\mathrm{ind}}$) to the shock propagator in the upper regime; the threshold is world commodity price. (**b**) The response of inflation in Indonesia ($\mathrm{infl}_t^{\mathrm{ind}}$) to the shock propagator in the lower regime; the threshold is world commodity price. Note: Above the zero line responds positively. Below the zero line responds negatively.

Table 7. Summary response variable due to impulse variables $\mathrm{gdp}_t^{\mathrm{w}}$, $\mathrm{infl}_t^{\mathrm{w}}$, and $\mathrm{comm}_t^{\mathrm{w}}$.

Response	Threshold	Regime	Figure	Impulse of $\mathbf{gdp}_t^{\mathbf{w}}$	Impulse of $\mathbf{infl}_t^{\mathbf{w}}$	Impulse of $\mathbf{comm}_t^{\mathbf{w}}$
$\mathrm{gdp}_t^{\mathrm{ind}}$	$\mathrm{gdp}_t^{\mathrm{w}}$	Upper	4a	0(0–1), +++(2–5)	++(0–5)	0(0–5)
		Lower	4b	0	0(0–5)	0(0–5)
$\mathrm{inf}_t^{\mathrm{ind}}$	$\mathrm{gdp}_t^{\mathrm{w}}$	Upper	5a	++(0), 0(1), −−(2–5)	0(0–5)	0, ++(1–3), −(4–5)
		Lower	5b	++(0), +(1–5)	0: −−(1–5)	0, ++(2–5)
$\mathrm{inf}_t^{\mathrm{ind}}$	$\mathrm{infl}_t^{\mathrm{w}}$	Upper	6a	++(0), +(1–5)	0	0:++(1–2), 0(3–5)
		Lower	6b	+, ++(1–5)	0: −−(1–5)	0:++(1–2), 0(3–5)
$\mathrm{gdp}_t^{\mathrm{ind}}$	$\mathrm{comm}_t^{\mathrm{w}}$	Upper	7a	+ (0), 0: −−(2–5)	0(0–5)	0(0–5)
		Lower	7b	+ (0–2), 0 (3–5)	0(0–5)	0(0–5)
$\mathrm{inf}_t^{\mathrm{ind}}$	$\mathrm{comm}_t^{\mathrm{w}}$	Upper	8a	0(0–1), +++ (2–5)	0(0–5)	0:+(1–5)
		Lower	8b	+(0), −(1), + (2–5)	+(0), −(1), + (2–5)	0(0) to ++(1–5)

If the world economy is viewed from the level of world commodity prices, Indonesia's GDP response is higher at low world commodity prices. At the high level of world commodity prices, at the beginning of the period, Indonesia's inflation did not respond at all. An increase in Indonesia's inflation occurs in the next 2–5-month period. An inflation increase in Indonesia occurs at both the low and high levels of world commodity prices; this shows that the changes in world commodity prices affect Indonesia's inflation response after a certain period. This increase occurs at all levels of world commodity prices.

If viewed from the shock of world inflation, Indonesia's GDP response and inflation are generally very small, even showing no change in response. If viewed from the shock of world commodity prices, Indonesia's GDP response and inflation Indonesia are also very small at the beginning of the period; however, they will increase after a certain period of time. The phenomenon of response change in the inflation does not show the same pattern due to the shock of world commodity prices; rather, it shows an increase in the next 1–2 periods, then disappears in the next 3–5 periods.

5. Conclusions

Threshold regression calculates a lower SSR value than threshold-free regression. Threshold regression takes into account the non-observed factor of exogenous variables within or beyond the model. The SSR values of the commodity index and global GDP are smaller than those of other regressions, depending on different thresholds.

The impulse simulation of world GDP gdp_t^w produces a positive response towards Indonesia's GDP and Indonesian inflation, in both the upper and lower regimes of gdp_t^w, $infl_t^w$, and $comm_t^w$. Impulse simulation of world inflation $infl_t^w$ does not show any response in Indonesia's GDP or inflation in the upper and lower regimes of gdp_t^w, $infl_t^w$, and $comm_t^w$.

Meanwhile, impulse simulation of world commodity prices $comm_t^w$ shows no response of Indonesian GDP gdp_t^i in either the upper or lower regimes of gdp_t^w, $infl_t^w$, and $comm_t^w$. The impulse simulation of the responses of world commodity prices $comm_t^w$ to Indonesia's inflation shows diverse patterns; positive responses occur after the next 1–3 periods. This conclusion is consistent with the research of Galih and Safuan (2018); in their research, Indonesia's GDP gdp_t^i did not respond to in either the upper or lower regimes of gdp_t^w, $infl_t^w$, and $comm_t^w$.

World GDP rate gdp_t^w and world inflation rate $infl_t^w$ play important roles in increasing Indonesia's GDP and inflation. The commodity price level of the world $comm_t^w$ generally affects several periods after the shock occurs, indicating that world commodity prices play an important role in increasing Indonesia's GDP and inflation in a given period. Baek (2021) states that world economic growth and world inflation affect the development of inflation and Indonesia's GDP. Khan and Senhadji (2000) also found threshold effects in the relationship between inflation and growth.

The most significant world GDP threshold is 3.2%; this indicates significantly that at a 3.2% world GDP rate, there are changes in Indonesia's GDP response behavior and Indonesian inflation. World inflation of 10.5% indicates that a global inflation rate of this magnitude will make Indonesia's inflation behavior undergo a structural change. World commodity prices of 2.3% indicate that such an increase in world commodity prices will cause changes in the GDP response and inflation of Indonesia. A study that mentions structural changes were carried out by Chowdhury and Ham (2009); their study applied inflation and growth, and found that there was a structural shift in both. Different responses occurred in the two regimes.

Global liquidity has no impact on Indonesia's GDP at various levels of global GDP and global inflation. The effect on Indonesia's GDP on regional economic factors varies depending on inflation and world GDP. This result is supported by the study of Djigbenou-Kre and Park (2016), where the results show that global liquidity has an effect on global imbalances. We can thus conclude that the global economy does not have a balanced and equitable effect on all countries in the world, including Indonesia.

World GDP continues to play a role in ASEAN's regional change, particularly when it comes to affecting Indonesia's GDP. The volatility of the world economy does not influence Indonesia's economic growth. This outcome is demonstrated by the insignificant effect of many independent variables. World inflation continues to be a major changing factor in the ASEAN region, especially in terms of affecting Indonesia's output. This is consistent with the growth of monetary policy, which aims to preserve the level of inflation in developing nations.

This research faces various limitations. One of the limitations of the VAR model is the use of IRF analysis. The response depicted on the graph can occur, assuming that there is no change in economic conditions over time. In fact, changes in economic variables occur very often, and those variables affect one another. Therefore, the analysis described is focused on the initial response period.

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Regional Stock Exchange Development and Economic Growth in the Countries of the West African Economic and Monetary Union (WAEMU)

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Abstract: This study used panel data covering 27 years to investigate the causality between regional stock exchange development and economic growth in the West African Economic and Monetary Union (WAEMU) countries. We performed a homogeneous Granger non-causality with an autoregressive distributed lag model (ARDL) and Markov-switching analysis, using six indicators for the stock and financial market and six for control. The results showed a close economic relationship between WAEMU countries and causality from the regional stock exchange, which supports the supply leading hypothesis. The causality was confirmed in the short and long run, depending on the variable. The causal relationships that support the demand-driven hypothesis were recorded from the economic growth for four market measurements.

Keywords: BRVM; WAEMU; regional stock exchange; economic growth; developing countries

JEL Classification: E44; G10; O43

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1. Introduction

Financial market conditions are usually linked to a country's political and economic conditions. Developed countries have an established market or trade in well-developed markets, whereas emerging financial markets belong to developing countries. Further, pre-emerging markets, or frontier markets, are those belonging to less developed countries. Almost every developed country has many financial services provided by a multitude of institutions operating in a diversified and complex network, which together make up the financial system.

However, in developing countries, the financial system offers shorter ranges or lower-quality services. Today, in developing countries, development of the financial system is considered an excellent way to support economic growth and includes the development of financial institutions, financial markets, etc. Rao and Cooray (2011) found that for countries with lower incomes, but not for those with higher ones, there is a close relationship between future economic growth and stock exchange activity.

Most low-income countries are still at an early stage of development. With a low Gross Domestic Product (GDP) per capita, and a small population, these frontier market countries (Shum 2015) usually do not even have a domestic financial market. However, they can depend on or be influenced by stock exchange activities. Among these countries, some have established communities, such as the West African Economic and Monetary Union (WAEMU). Categorised as a frontier market (Morgan Stanley Capital International (MSCI) 2021), the WAEMU possesses a financial market known as the Regional Securities Exchange or the Bourse Régionale des Valeurs Mobilières (BRVM). As the saying goes, "United, we are stronger." WAEMU countries are neither financially stable nor economically strong enough to have different exchanges, and so by pooling resources they can safely navigate internationally.

The BRVM, the common exchange of the eight states (Benin, Burkina-Faso, Cote d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, Togo) of the WAEMU, is one of the very few exchanges worldwide that is regionally integrated and serves as the central exchange for a group of regionally related countries, as noted by Ganti (2019). Despite many challenges, it should be a pioneer for the further integration of the stock exchanges in Africa (James 2018). The eight member states of WAEMU are all developing countries, which are still considered low-income countries; hence, the impact of the regional stock exchange on their economy becomes important.

Another factor that should not be overlooked is what WAEMU countries have in common: they are all post-colonial states that are still under monetary control. They use a currency called the CFA franc (Franc of the African Financial Community). Assane and Malamud (2010) pointed out that the constraints of monetary unions affect the financial depth of the CFA countries and hurt economic growth. Koddenbrock and Sylla (2019) later found that the CFA caused extreme external repression of financial and monetary policies because of its dependence on the euro and the US dollar. The reason is that France prints the CFA for the CFA countries and is, therefore, able to control the financial and monetary regulations, the money supply, the credit allocation, the banking activities, and the economic and budgetary policies of these nations.

Moreover, as suggested by Tadesse (2018), this control breeds corruption and illegal diversion of public aid between France and its former colonies. For instance, conditional French public aid has forced these African states to spend the money destined for aid on French equipment, goods or contracts with French firms, especially construction and public work firms. Internally, the design of the CFA franc strengthens the constraints that are imposed on all bank–firm relations and central bank policies in the Global South and makes it more difficult to pursue growth strategies for the benefit of the broader population. The CFA franc is a heavy economic burden on WAEMU countries. To support these observations, Sow et al. (2020) explained that various financial development policies have been unsuccessful from independence (1960) to the present. As a result, economic development is slow, not to mention the existence of lasting economic precarity. WAEMU countries are facing an unprecedented economic dilemma stemming from their common currency, whereas, in contrast, most of the low- and high-income countries studied have independent currencies.

Given the interest in financial markets, the specifics of developing markets, and WAEMU countries, this study attempts to assess the existence and nature of the relationship between BRVM development and economic growth in WAEMU countries. To this end, a panel Granger non-causality procedure is conducted for the eight WAEMU countries, followed with an Autoregressive Distributed Lag model (ARDL) and a Markov-switching analysis.

The contribution of this paper to the empirical literature on stock exchange development and economic growth covers various aspects. First, it examines the WAEMU regional stock exchange, which has not been the subject of many studies up to now. Second, awareness is created concerning whether WAEMU countries should use the BRVM as an economy booster given their current level of development. Third, given the analysis process, cross-sectional dependence is considered for the causality approach, in order to avoid inconsistency and bias in the empirical results. To the best of our knowledge, no such attempt to include the cross-sectional hypothesis in the literature on stock exchange development and economic growth in the WAEMU countries has been made up to date. Fourth, financial development is known to be of a multidimensional nature. Thus, to capture the numerous aspects of the market in the economic development process, we utilize six indicators. Finally, the dataset contains eight countries for a period of 27 years, to abide by the well-known rule of thumb in economics which stipulates that a large dataset is necessary for a relevant panel data analysis.

The rest of this paper is divided into four sections: the literature review is outlined in Section 1. Section 2 presents the data, describes the variables and the empirical strategy. Section 3 presents the analysis and results. The conclusion is given in the last part.

2. Review of Literature

Long-run securities, such as bonds and shares, are among the services provided by capital markets. Several authors, such as Ewah et al. (2009) and Oke and Adeusi (2012), stated in their contributions to the literature that the capital market (comprising bond and equity markets) is the market in which medium- to long-term financing can be obtained. The purpose is to develop companies that, as a result, promote a nation's economic growth. Therefore, the existence of the capital market seems to be an economic booster. However, such an expected positive effect should differentiate between countries to avoid scientific bias, as economic realities differ from country to country.

Seven and Yetkiner (2016), who examined 146 middle- and high-income countries from 1991 to 2011, found a significant positive correlation between economic growth and stock exchange development. However, almost a decade earlier, Ben Ben Naceur and Samir (2007) had contradicting views on developments in financial markets and economic growth in middle-income countries. By examining a sample of 11 countries in the MENA (the Middle East and North Africa) region, they reported that the development of financial systems could harm economic growth. Later, Stephen and Enisse (2012) pointed out that financial booms rarely encourage growth and suggested re-examining the relationship between real growth and finance. Yu et al. (2012) were more specific, arguing that the positive relationship between growth and finance found in many studies is a long-run relationship. Regarding underdeveloped countries, they mentioned that these countries may face slower economic growth in the short run, although the stock exchange is developing, mainly because of political instability and poorly enforced legal systems. It can be observed here that the positive effect of stock exchange developments on economic growth, especially in the middle- and low-income countries, is shadowed by the negative impact of political instability and poor enforcement. Thus, depending on the size and direction of the changes, the positive effect may prevail, or the countries may face a slowdown in their economy in the short or long run.

With underdeveloped or low-income countries, however, some authors, such as Haque (2013), who examined the countries of the South Asian Association for Regional Corporation (SAARC), could show that stock exchange developments had no significant influence on economic growth. Rioja and Valev (2014) supported these findings. Using a large cross-country panel, they observed a significant positive impact on stock exchanges and capital accumulation in banks for high-income countries; however, banks have not contributed to productivity growth or capital accumulation in low-income countries. Here, the stock exchange development seems to have a neutral effect on economic growth, and thus we can conclude that capital markets are not among the best channels for economic development in developing countries.

This idea is supported by the findings of Ewah et al. (2009). Using multiple regression and ordinary least squares (OLS) on 44 years of data, they conducted a study on Nigeria and showed that the Nigerian capital market, although endowed with the ability to induce growth, has not contributed significantly to Nigeria's economic growth because of low market capitalisation, small market size, low transaction volume, illiquidity, and few listed companies, etc. Francis and Ofori (2015), working with data on 101 countries from 1980 to 2009, showed that political instability in some underdeveloped countries can hamper the development of stock exchanges and justify their ineffectiveness regarding economic growth because the stock exchange development is positively influenced by policy scores. Karim and Chaudhary (2017) also pointed out that while stock exchange developments contribute to South Asia's economic growth to some extent, their effect is negligible. A year later, Pan and Mishra (2018) concluded that there is no significant impact on economic growth in economies where the stock exchange plays a minimal role (large economies like China).

The preceding lines reveal two major pieces of information. Firstly, the positive or negative impact of the stock exchange on economic growth is to be observed in the long or short run, depending on the income level and political characteristics of the country. Secondly, in most cases, the development of the stock exchange plays an economically neutral role and can even be a hindrance.

Instead, some authors have looked only for a connection and have concentrated on analysing the causal relationship between economic growth and stock exchange developments. In Nigeria, Adamu and Sanni (2005) used regression analysis and the Granger causality test to assess the role of the stock exchange in economic growth in Nigeria. A one-way causality between market capitalisation and GDP and a two-way causality between market turnover and GDP growth was discovered. A significantly positive relationship between turnover ratios and GDP growth was also observed. This suggests that market turnover and turnover ratios are essential stock exchange proxies that impact economic growth.

In Nigeria too, Kolapo and Adaramola (2012) carried out a Granger causality and Johansen cointegration test. They discovered a long-run positive influence of the capital market on economic growth. Demirguc-Kunt et al. (2012) also showed that the development of banks and stock exchanges shows a parallel relationship with the economic growth of countries. Therefore, even if no direct causality is shown, it is evident that the development of stock exchanges and economic growth advance as a pair. Ikikii and Nzomoi (2013) confirmed this by examining the effects of the development of the stock exchange on economic growth in Kenya. Using quarterly time-series data, they found that stock exchange developments had a positive impact on economic growth.

Mittal (2014) also found strong indications of an existing causality in his search for a causal relationship between economic growth and the stock exchange in the newly industrialised countries (NIC). He suggested that the governments of these countries should better direct monetary and fiscal policies towards promoting the growth of the financial sector. Later, Milka (2021) carried out a similar analysis in Serbia. With the Toda-Yamamoto-Dolado-Lütkepohl approach for the Granger causality test, the vector autoregression model, the forecast error variance decomposition, and the impulse response function, he demonstrated the existence of a unidirectional Granger causality from stock exchange development to economic growth.

Similarly, Maku (2020) used an autoregressive distributed lag model (ARDL) bound test and examined the relationship between the development of stock exchanges and economic growth in Nigeria. The empirical results confirmed the existence of a long-run relationship between stock exchange development and growth. Ezeibekwe (2021) used a vector error correction model and concluded that using the ratio of market capitalisation to GDP as a proxy for stock exchange development does not contribute significantly to economic growth in Nigeria in the long run. This finding implies that the Nigerian economy is still at a stage of development where the stock exchange cannot play a crucial role in economic development.

It is evident that there are still contradictory views regarding the relationship between stock exchange development and economic growth, even though the causal effect of the stock exchange on the economy, especially in underdeveloped countries, has been confirmed by most studies. This hypothesis of the causal effect of stock exchange development on the real economy belongs to supply leading theory.

This theory suggests that the accumulation of financial assets improves economic growth; therefore, the development of the financial markets will lead to positive economic growth (McKinnon 1973; Shaw 1973). As observed in some studies, the results sometimes suggest an economy to stock exchange causality or a reverse relationship between the stock exchange and economic growth. This gives rise to another hypothesis, expressed as the demand-driven hypothesis, by Friedman and Schwartz (1963). They suggested that economic growth brings with it the emergence and establishment of financial centres. Simply put, the growth of the real economy endogenously determines financial development. These two theories are part of others drawn from decades of research into the finance–growth nexus. Fink et al. (2006) pointed out that the nexus between the real economy and the financial market can be summarised in five forms: supply leading, demand-driven, no causal relationship, interdependence, and negative causality from finance to growth.

One reason for the ambiguity in the existing literature about the financial growth nexus issue could be the proxies used for the stock exchange and the real economy. Using one or two proxies is too restrictive to capture different aspects of the market. As often used, gross domestic product (GDP) also measures an annual global or individual level of production instead of the actual economic growth trend. Another reason may be the geographical limitations and economic diversity of countries. Most studies relate to specific countries and rarely to groups of countries with a financial market. Even if different countries are included in panels, they are often heterogeneous. Most of the countries examined so far have also been economically independent with a local currency, unlike WAEMU countries, which still use a common currency, often referred to as colonial money.

Given the peculiarities of the WAEMU context, this paper seeks to determine whether WAEMU countries will benefit from having a financial market. We also test demand-driven and supply-driven hypotheses

3. Research Data, Materials, and Methods

3.1. Data Source and Type

The first steps of the BRVM can be traced back to 14 November 1973 when the treaty establishing the WAEMU was signed. Members included Burkina Faso, Benin, Côte d'Ivoire, Niger, Mali, Togo, and Senegal. In 1997, Guinea-Bissau joined, and to date there are eight member countries. On 17 December 1993, the WAEMU Council of Ministers set up a regional financial market and commissioned the West African Central Bank (WACB), known as Banque Centrale des États de l'Afrique de l'Ouest (BCEAO) in French, to manage the project.

Introducing the market regime in 1997 gave investors more confidence and helped stimulate business. With e-commerce and the transition to daily basic trading (1999–2001), a steady increase has been observed since 2000. As Proshare (2010) reported, many years of reforms caused significant changes in 2011 and 2013, and saw a sharp decline in operations, with the market recovering and booming in 2012. Since then, the BRVM has experienced a stable evolution.

Pan and Mishra (2018) found that most time-series research used a short sampling period because of data limitations. This problem is more pronounced in developing countries where obtaining data is quite a challenge. This study also deals with this problem, even though the focus is on panel data. While updated time-series data can be obtained for most of the companies listed on the BRVM, countries updated market data remain a challenge. The data used in this study were obtained for each WAEMU country from the World Bank (Global Financial Development Database, World Development Indicators Database, and World Governance Indicators Database) and the International Monetary Fund (Financial Development Index Database). The first data collected covered from 1971 to 2020. Data were then filtered variably. For some variables, data were not available as early as 1989, and the last update for some variables was before 2016. Therefore, after filtering, the final data set contained observations from 1989 to 2015.

3.2. Stock Exchange and Other Variables

The model used was, like that of Mohtadi and Agarwal (2007), a modified and improved version of the well-known model by Levine and Zervos (1998). The first specificity of this improved model is to overcome the measurement and consistency problem associated with the use of two different data sources by Levine and Zervos (1998). Although the present study uses different data sources, they are filtered and combined into one single final dataset for analysis. Moreover, the data sources are interconnected, which guarantees the consistency of our data. Second, this model uses several measures of stock exchange development to maximize the use of information extracted from the data, as opposed to a single composite measure. It enables the economic growth in year t to be estimated as a function of the stock exchange development in year t-1.

This study also used several proxies of the stock exchange development to optimally employ the information obtained from the data instead of a single composite measure. However, some financial indices were added individually to represent the development of both the financial market and of the stock market. The purpose was to capture different aspects of the market and create more space for relevant results to be achieved. The PSE (primary school enrolment) variable was also added to the model, along with CC (corruption control) and OP (oil prices). WAEMU countries face many challenges in primary and secondary education. In a 2015 education report, the Africa-America Institute (AAI) mentions that many African countries cannot keep up with rising enrolments, the results of which are that the learning outcomes have been negatively impacted (Africa-America Institute (AAI) 2015). Therefore, governments need to invest in educational innovation to improve the quality of education in schools. The variables were the following:

- Stock Market Capitalisation (SMC): This results from the market capitalisation of listed companies divided by GDP.
- Shares Traded Total Value (STTV): This represents the value of the shares traded and the total market capitalisation above GDP.
- Stock Market Turnover Ratio (SMTR): This is measured as the market capitalisation of listed companies (MCLC) divided by the total market capitalisation (TMC).

Three variables for financial development were taken from the financial development index database and used in this study, as follows:

- Financial Markets Access Index (FMA): This represents the level or degree of accessibility of the market by individuals, companies, and countries to raise funds, invest in the market, etc.
- Financial Markets Depth Index (FMD): This represents the depth of the market or its ability to take large orders without significantly impacting the prices of the securities.
- Financial Development Index (FD): This represents the level of development of the market.

Information for the remaining variables was collected from the World Development Indicators database:

- Growth: This measure represents the annual growth rate per capita and was used as a dependent variable.
- Foreign Direct Investment (FDI): Since FDI is considered a determinant of economic growth, it is used as a control variable. In this study, the variable was the value of net FDI divided by GDP.
- Investment (INV): Investments are defined as real investments divided by GDP.
- Primary School Enrolment (PSE): PSE was represented as a percentage of the total population.
- Corruption Control (CC): CC captures the perception of the extent to which public power is exercised for private gain. The values were estimates (in units of a standard normal distribution) of the country's score on CC.
- Oil Prices (OP): OP represents the pump prices of the best-selling grade of gasoline.
- Inflation (INF): INF shows the rate of change in prices in the economy. This variable was used because of the special situation that WAEMU countries have (sharing a common colonial currency, namely the CFA franc). WAEMU member countries were once French colonies. After their independence, among other agreements, they have kept a currency that is printed and entirely dependent on France, their former colonist. Thus, the CFA franc is called colonial currency. Some studies have analysed the parity of the fixed exchange rate between the French franc (FF) and the CFA franc (FCFA),

as this exchange rate does not reflect the economic fundamentals of the countries it should serve (Des Adom 2012). Given also the increasing globalisation of financial markets, raw materials, and volatile oil prices, the CFA franc faces challenges, such as significant changes in export prices and a prolonged genuine appreciation of the currency (Gulde and Tsangarides 2008).

3.3. Model Specification

According to Mohtadi and Agarwal (2007), the original approach enables control for countries as a block and each country specifically. It is divided into two models: the first model tests whether the stock exchange affects economic growth, and the second examines their relationship. However, our approach was slightly different in that we only checked for the entire region. This is because the WAEMU states have a unique stock exchange that pools the countries' financial market investments.

Checking for country-specific observations would also have meant a small sample of observations over 27 years. As a result, a country-specific process in WAEMU countries could have resulted in biases. We only used one model and directly investigated the relationship between regional financial market development (with an emphasis on stock exchange development) and economic growth in WAEMU countries.

Here, the growth (as a dependent variable) at time t was a function of the other variables at time $t - 1$. Our analysis was based on the following panel data model:

$$y_{it} = \beta_j + \sum_{j=1}^{k} \beta_j X_{ji(t-1)} + c_i + \delta_{t-1} + \varepsilon_{i(t-1)} \quad (1)$$

where i represents the unit of observation, t indicates the time, j is the observed explanatory variables, t is the time trend, and δ signifies the implicit assumption of a constant rate of change. y stands for the dependent variable and X for the independent variable (k is up to 12 in this study). c represents the unobserved effect, and ε is the error term. β are the individual intercepts or slope coefficients that can differ across the states.

We reinforced the model with a step-by-step analysis process that compensated for our dropping of model 1 by Mohtadi and Agarwal (2007) and made the results more robust. For the analysis process, the steps recommended by Menegaki (2019) to implement an ARDL were followed. This procedure was chosen because it is a step-by-step sequence that guarantees control of model misspecifications and more relevant results. The approach of Mohtadi and Agarwal (2007) has long since been proven efficient, but the economic case of the WAEMU requires more precision. With the additional variables in the model (both stock and financial market) and considering the improvement of econometric measurements in the scientific literature, traditional analysis procedures (regression, correlation tests, etc.) may not be enough. Therefore, it was applied in the ARDL procedure. The ARDL is a step-by-step procedure in which the next test to apply depends on the results from the previous test; thus, the final results are more precise. The first stage of the analysis was a cross-sectional dependency test, the second stage was a stationarity test, the third stage was a cointegration test (for non-stationarity), and the last step was a causality test. After these steps, an actual ARLD regression with structural break control was implemented to check the robustness. The control of structural breaks was important to our analysis because of many global events (such as the Afghanistan and Iraq wars, the Asian financial crisis, the attacks on the World Trade Centre, and the 2008 Global Financial Crisis), which occurred during our sample period. We completed our analysis process by performing a dynamic regression (Markov-switching regression).

4. Data Analysis, Results, and Discussion

The details of the data for each variable are shown in Table A1. Negative values can be observed for Growth, CC, INV, FDI, and INF in WAEMU countries. Figures A1 and A2 in the Appendix A Table A1 give a visual representation of the evolution of economic growth along with the stock and financial market variables in each of the WAEMU countries. A quick look at the figures does not seem to show that growth for any WAEMU country followed the same trend as other variables. However, higher stock market capitalisation (SMC) appears to be associated with higher economic growth.

We had an overall observation of 216 per variable with T = 27 and N = 8. Where T is small and N is large (the common situation when analysing panel data), a Pesaran test, a Friedman test, or a Frees test (Friedman 1937; Frees 1995, 2004; Pesaran 2004) are better adapted, but if T > N, the Lagrange Multiplier (LM) test by Breusch and Pagan (1980) is well suited to test the cross-sectional dependency (CD) (see Equation (2)).

$$LM_{BP} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{P}_i^2 \tag{2}$$

where $\hat{P}_i^2$ is the estimated correlation coefficient between the residuals derived from the panel model estimate. Under H0, there is an asymptotic chi-square distribution (chi2) concerning the LM statistic with a degree of freedom of $N\,(N-1)/2$. i, j, and T are derived from the panel model equation, with t = 1, 2, ..., T.

As shown in Table A2, the results suggest the rejection of the null hypothesis; there was a correlation between the panels' attributes. This means that any shock in one of the WAEMU countries will be transmitted to others. In line with Pesaran and Yamagata (2008), we also checked the nature of our panels.

The slope homogeneity null hypothesis H0 is $\beta i = \beta$ for each is compared to the heterogeneity hypothesis H1: $\beta i \neq \beta j$ for pair-wise slopes non-zero fraction for $i \neq j$.

Pesaran and Yamagata (2008) developed standardised dispersion statistics that cover a broader spectrum of analysis. In contrast to Swamy's (1970) model, which is only limited to models where N is relatively smaller than T, it takes the Pesaran and Yamagata model into account and extends it to wider panels. The model is represented as:

$$\widetilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\widetilde{s} - k}{\sqrt{2k}}\right) \tag{3}$$

with $\widetilde{s}$ being a modified version of Swamy's (1970) slope homogeneity test.

$$\widetilde{s} = \sum_{i=1}^{N}\left(\ddot{\beta}_i - \hat{\beta}_{WFE}\right)\frac{x_i'M_\gamma x_i}{\widetilde{\sigma}_i^2}\left(\ddot{\beta}_i - \hat{\beta}_{WFE}\right) \tag{4}$$

where $\ddot{\beta}_i$ represents the pooled OLS estimator, $\hat{\beta}_{WFE}$ is the pooled estimator of the weighted fixed effect, M_γ is an identity matrix, and $\widetilde{\sigma}_i^2$ is the estimator of σ_i^2.

In addition, the $\widetilde{\Delta}$ test's small sample properties can be improved with normally distributed errors by using the following variance and mean bias-adjusted version:

$$\widetilde{\Delta}_{\dot{a}dj} = \sqrt{N}\left(\frac{N^{-1}\widetilde{s} - E\left(\widetilde{z}_{\dot{i}t}\right)}{\sqrt{var\left(\widetilde{z}_{\dot{i}t}\right)}}\right) \tag{5}$$

with $E\left(\widetilde{z}_{\dot{i}t}\right) = k$, and $var\left(\widetilde{z}_{\dot{i}t}\right) = 2k(T-k-1)/(T+1)$.

The analysis result (Table A2) did not reject the null hypothesis of homogeneous coefficients. Therefore, in the WAEMU area, there will be replication in other countries of every significant economic relationship or change in one country.

From the previous analysis, we could have gone straight to a bootstrap panel Granger causality according to Kónya (2006); however, this requires cross-sectional dependency and cross-border heterogeneity, which was not the case for us.

Following the analysis, four tests—Hadri Lagrange, Levin Lin Chu, Im-Pesaran-Shin, and Fisher—(Hadri 2000; Levin et al. 2002; Im et al. 2003) were carried out to check the stationarity; this provided information about the degree of integration for each variable.

As shown in Table A3, only Growth, SMTR, FD, OP, FDI, and INF were stationary. By computing the first difference, the stationarity for SMC, STTV, FMA, FD, CC, INV, and PSE was restored.

The non-stationarity of some variables suggests a long-run relationship between them that can affect growth. Therefore, a little digression into cointegration analysis is necessary. Since there are multiple cointegration tests and remembering that our panels were homogeneous (Table A2), the best option was that of Kao (1999), which allows five sets of tests specifically designed for homogeneous panels to be performed. Kao's cointegration test can be carried out together with those of Pedroni (1999) and Westerlund (2005). However, since the Westerlund test assumes heterogeneous coefficients, it did not fit into our context. Pedroni's test assumes both homogeneous and heterogeneous coefficients. Therefore, besides the Kao test, we also carried out the Pedroni cointegration test. Both tests' results confirmed the cointegration (Table A4).

For further analysis and to take robustness into account, we performed a dynamic ordinary least squares (DOLS) regression.

The fully modified ordinary least squares (FMOLS) regression was developed by Phillips and Hansen (1990), and later Stock and Watson (1993) developed the DOLS. These models help generate coefficients that are asymptotically efficient because they consider both serial autocorrelation and endogeneity. They are only used if the variables are stationary at the first difference. The ordinary least squares (OLS) regression is often skewed when the variables are non-stationary and cointegrated, while DOLS and FMOLS are not. However, FMOLS is designed and works well with heterogeneous data, while DOLS offers more flexibility. Because of our data, we only had a DOLS regression.

As can be seen in Table A5, there was a significant and positive long-run relationship between stock and financial market variables and growth, except for STTV, which hinders growth over the long run. The control variables (except for OP and FDI) also showed significant long-run relationships with growth. CC, INV, and PSE contribute to economic growth, while INF does not. These results reflect reality since the reduction of corruption reduces the loss of money and allows the perfect implementation of projects and policies, thus improving the economy. The more investment, the more employment and increased economic activity. As for education, it is the very basis for any nation; and it starts from primary school. Based on these first observations, one might be tempted to say that stock exchange developments are contributing to economic growth in WAEMU countries; however, such a conclusion would be far too easy.

We proceeded with a causality analysis by running a Granger non-causality test. The most widely used Granger causality tests are designed for heterogeneous panels. Juodis et al. (2021) proposed a novel approach that helps perform a Granger non-causality test in both heterogeneous and homogeneous panels that best fit our data. Table A6 shows the outcome of the Granger non-causality test.

A first test was performed with Growth as the dependent variable; then reverse causality was implemented to assess the effect of Growth on each of the dependent and control variables. There was a one-way causality between FMA and FMD to Growth and from Growth to INV. For the other independent variables and control variables, a bidirectional causality was observed in Growth.

According to the results so far, the financial market (the BRVM) is linked to economic growth and contributes to this in WAEMU countries. This conclusion is supported by the results of the DOLS regression, which showed significant long-run relationships between Growth and SMC, STTV, SMTR, FMA, FMD, and FD. The only negative relationship observed over the long run was with STTV, which showed significance at the 1% level (Table A5). The results also confirmed the supply-leading hypothesis for the stock and financial markets (all six variables cause growth); in other words, the development of the stock and financial market contributes to economic growth. The demand-driven hypothesis was confirmed for the stock exchange (the three stock exchange variables were caused by Growth versus one in three for the financial market variables); that is to say, the increase of the economy significantly participates to the improvement of the stock exchange, and somewhat to the development of the financial market.

Regarding the control variables, although INV had a long-run relationship with Growth, it had no causality. The remaining control variables (CC, OP, FDI, PSE, INF) Granger caused growth (Table A6); meaning that they have an impact on the economy. The positive impact of CC is not surprising, as better anti-corruption policies will lead to a healthier economy in the long run.

After the causality analysis, an ARDL regression was implemented. Since the number of the ARDL's regressive variables was limited, we split our original model into two equations for its application. We outline our ARDL representation in Equation (6) for stock and financial market variables and in Equation (7) for control variables.

$$\mathrm{Growth_t} = \beta_0 + \Sigma\beta_i \mathrm{SMC}_{t-i} + \Sigma\beta_j \mathrm{STTV}_{t-j} + \Sigma\beta_k \mathrm{SMTR}_{t-k} + \Sigma\beta_l \mathrm{FMA}_{t-l} + \Sigma\beta_m \mathrm{FMD}_{t-m} + \Sigma\beta_n \mathrm{FD}_{t-n} + \varepsilon_t \quad (6)$$

$$\mathrm{Growth_t} = \beta_0 + \Sigma\beta_i \mathrm{CC}_{t-i} + \Sigma\beta_j \mathrm{OP}_{t-j} + \Sigma\beta_k \mathrm{INV}_{t-k} + \Sigma\beta_l \mathrm{FDI}_{t-l} + \Sigma\beta_m \mathrm{PSE}_{t-m} + \Sigma\,\beta_n \mathrm{INF}_{t-n} + e_t \quad (7)$$

where i, j, k, l, m, and n are the number of lags for the independent variables in the models. Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC) were used to determine the optimal lag number and the ARDL (1,0,0,0,0,4) was chosen for both equations. We then formulated our unrestricted error correction models:

$$\begin{aligned}\Delta\mathrm{Growth_t} = \beta_0 \; & + \Sigma\beta_i \Delta\mathrm{Growth}_{t-i}\, \Sigma\beta_j \Delta\mathrm{SMC}_{t-j} + \Sigma\beta_k \Delta\mathrm{STTV}_{t-k} + \Sigma\beta_l \Delta\mathrm{SMTR}_{t-l} + \Sigma\beta_m \Delta\mathrm{FMA}_{t-m} \\ & + \Sigma\beta_n \Delta\mathrm{FMD}_{t-n} + \Sigma\beta_o \Delta\mathrm{FD}_{t-o} + \gamma_1 \mathrm{SMC}_{t-1} + \gamma_2 \mathrm{STTV}_{t-2} + \gamma_3 \mathrm{SMTR}_{t-3} + \gamma_4 \mathrm{FMA}_{t-4} \\ & + \gamma_5 \mathrm{FMD}_{t-5} + \gamma_6 \mathrm{FD}_{t-6}\, \varepsilon_t\end{aligned} \quad (8)$$

$$\begin{aligned}\Delta\mathrm{Growth_t} = \mu_0 \; & + \Sigma\mu_i \Delta\mathrm{Growth}_{t-i}\, \Sigma\mu_j \Delta\mathrm{CC}_{t-j} + \Sigma\mu_k \Delta\mathrm{OP}_{t-k} + \Sigma\mu_l \Delta\mathrm{INV}_{t-l} + \Sigma\mu_m \Delta\mathrm{FDI}_{t-m} + \Sigma\mu_n \Delta\mathrm{PSE}_{t-n} \\ & + \Sigma\mu_o \Delta\mathrm{INF}_{t-o} + \Delta_1 \mathrm{CC}_{t-1} + \Delta_2 \mathrm{OP}_{t-2} + \Delta_3 \mathrm{INV}_{t-3} + \Delta\gamma_4 \mathrm{FDI}_{t-4} + \Delta_5 \mathrm{PSE}_{t-5} + \Delta_6 \mathrm{INF}_{t-6}\, e_t\end{aligned} \quad (9)$$

We estimated long- and short-run coefficients. The long-run relationship results of the DOLS analysis were robust with the ARDL results. Therefore, only the ARDL results for the short-run relationship were reported (Table A7).

From the observation of Table A7, we see that only STTV and SMTR had a significant positive relationship to Growth in the short run at the 1% and 5% levels, respectively; so a one point increase in the SSTV (SMTR) increases growth by 11.4781 (0.7832) points in the short run. So while STTV promotes growth in both the short and long run, SSTV hinders growth in the short run and promotes it in the long run. Other stocks and financial market variables do not appear to impact economic growth in the short run. As for the control variables, CC, OP, and FDI had a significant negative relationship to growth in the short run; any increase in point in this variable will reduce economic growth. The short-run negative effect of CC is understandable because the West African states have been under the influence of Western countries for decades and still leave the doors open to mismanagement of the countries' economic resources. A sudden breakdown of corruption in these countries will undoubtedly shake the system and affect the economy in the short run. However, the equilibrium is restored over time for the benefit of citizens and the economy, as shown by the positive long-run results (Table A5). This long-run horizon may be difficult to estimate at present since WAEMU countries are still under the yoke of France, which steers policies from outside. It implies that corruption control is unlikely to be effective at the high level of government decision-making. The short-run effects will be those observed outside of the government system's core: the part which is directly connected to the population, and which explains the immediate negative impact on the economy. Only INV, PSE, and INF had no short-run impact on economic growth. One comment on OP is that most WAEMU countries are oil price takers, and the few countries that produce cannot set prices at will because they are post-colonial states. Post-colonial states are de jure independent but are constrained by their economic systems so that policy is steered from outside (Ian 2019).

It seems understandable that if a negative effect on the economy is observed in the short run, no recognisable effects are to be expected in the long run. The negative impact of FDI in both the short and long run can be explained by the fact that foreign investment is mainly aimed at capitalising on the weaknesses of WAEMU countries and serving Western countries. Concerning PSE, it is widely used in assessing economic growth in underdeveloped or developing countries. Primary education is the foundation for any government to upgrade and improve its educational level, and our results confirmed its importance to the economy. The real benefits of primary education can only be seen in the long run. Our inflation results were contrary to those of Barcola and Kebalo (2018). They found that inflation does not affect economic growth in West Africa and has a positive effect on the economy within a certain threshold. While some economically independent West African countries, such as Ghana, Nigeria, etc., could benefit from INF, our results demonstrate that in WAEMU countries, inflation significantly hinders economic growth in the long run. This can be explained by the fact that WAEMU member countries, as mentioned earlier, are using a colonial currency. Since that currency limits them, they do not receive direct shocks from the international price movements and are literally in a state of "stability." Thus, the impact of inflation on the economy will take longer to be observed, compared to economically independent countries.

The diagnostic checks showed that there was no serial correlation and heteroscedasticity. The three tests carried out to control structural breaks also yielded negative results; namely, they confirmed the null hypothesis of no structural breaks over the study period (Table A7).

We complemented our static analysis with a dynamic analysis using a Markov-switching dynamic regression. Although the WAEMU's regional stock exchange shows no structural break, there may be times of regime changes (international or regional) that will affect the market and the economy. We assume two regimes in the economy: high and low volatility. According to Bautista (2003), the state of volatility comes from an unobserved first-order Kth state Markov process. It can be described by transition probabilities.

$$p\left(s_t = \frac{k}{s_{t-1}} i\right) = p_{ij} \tag{10}$$

With P_{ij}, the probability is that state i will be followed by state j. Ertugrul and Ozturk (2013) later specified that for the first-order Markov assumption it is necessary that the probability of being in a state depends entirely on the previous state. The simplified transition probability matrix, according to Coskun Yener et al. (2017), is shown in Equation (11) below:

$$p = \begin{vmatrix} \underline{p_{11}} \; \underline{p_{21}} \\ p_{12} \; p_{22} \end{vmatrix} \text{ where } \textstyle\sum_{j=1}^{2} p_{ij} = 1 \tag{11}$$

As can be seen from Table A8, the dynamic regression confirmed the findings of the static analysis. SMC promotes economic growth in the long run but can hinder it in a system with high volatility. STTV has a short-term positive influence on economic growth with high volatility and in the long run a negative impact on growth with low volatility. SMTR contributes to economic growth in the short and long run with high and low volatility. FMA, FMD, and FD all promote long-run economic growth with low and high volatility regimes, respectively. Details of other variables can be found in Table A7.

From the above analysis, the study's results show that WAEMU member countries are homogeneously interconnected. Similarly, their financial and real sectors are interdependent. The individually addressed regional stock exchanges and the globally considered financial markets are closely connected to WAEMU's economic growth. All the stock and financial market proxies cause (contribute to) economic growth, and a bidirectional causality has been observed between economic growth and the stock and financial market proxies, except for financial market access and depth.

The study has revealed that the stock exchange is driving economic growth in the region, which is very important. Only STTV hinders economic growth in the long run with low volatility regimes. Financial markets are driving economic growth globally. Increased FMA, increased FMD, and FD will contribute to WAEMU's economic growth in the long run. These observations suggest that the development of BRVM and its stock exchange play an important role in boosting the economies of WAEMU countries.

In the long run, measures must also be taken to prevent or undo the negative effects of the STTV.

In the remaining variables, we found that INV does not cause (has no impact on) economic growth in WAEMU countries, despite having long-run positive relationships with WAEMU countries. FDI and OP cause (lead to) economic downturns in the short run, and INF impedes economic growth in the long run.

The impact of CC in WAEMU is negative in the short run but positive in the long run. Primary school education (PSE) has no impact on growth in the short run but has a significant positive impact in the long run.

5. Conclusions

The relationship between economic growth and financial development remains a hot topic for extensive research and debate. The existence of a causal relationship between financial development and economic growth is still unknown. The available literature that proves the existence of causality remains uncertain regarding the direction of the causality.

This paper has examined the direction of the causal relationship between stock exchange development and economic growth in eight WAEMU countries that have shared a unique stock exchange (BRVM) for 27 years. The applicable methodology was Granger's non-causal relationship, completed by ARDL and Markov-switching analysis.

The study reveals that WAEMU member countries are not simple members of the Union but are all interconnected. Any significant economic situation in one country will reverberate on other countries. Further, the regional stock exchange is confirmed to be a major participant the economic development of WAEMU countries. The level of market capitalization, the value of share traded and the market turnover contribute to boosting the regional economy. In return, the growth of the economy contributes to the development of BRVM. The index of financial development further confirms this mutual relationship between BRVM development and WAEMU economic growth. Thus, it is a call for the eight countries' governments to work hand in hand with institutional and individual investors to guarantee a healthier development of the regional stock exchange for a better economy. Increased investment on the stock exchange is a key economic booster for the WAEMU member countries.

As access to the financial market is also important to boost the stock exchange activities and further promote the economy, governments should put more efforts into sensitizing the populations regarding financial investment and the use of the regional stock exchange. A sad reality of frontier markets is that, due to the low-income, the larger part of the population is focus on its day-to-day survival and is not educated for financial investment. The result is that, unlike developing or developed countries, most of the investors of BRVM are institutional, and very few are individuals.

It is well known that the WAEMU government uses financial markets to raise funds for public projects and investments, but these funds are often raised through the bond market. For example, WAEMU member countries mobilised US $17 billion in the regional money markets in 2020. The Republic of Benin alone completed one and set a record as of early January 2021 with a Eurobond issuance of 1 billion euros in the international bond market (Ecofinagency 2021a, 2021b). Given the importance of the stock exchange, the WAEMU government needs to rethink the activities of the regional stock exchanges and pay close attention to the optimal use of the stock exchange for the economic development of the country. This should start by raising awareness and educating the populations for investment in the regional stock exchange. Following this, measures should be taken to increase and facilitate market access to both individuals and institutional investors. More efforts should also be put into increasing the market depth for BRVM.

In the same perspective, WAEMU governments should gradually aim at giving priority to BRVM as financial partner and consider leaving the grip of the colonial currency. As observed, investments in WAEMU member countries do not promote economic growth, because most of the funds raised for projects or local development come from foreign investors, partners, or foreign companies. This also explains why when foreign direct investment is added, it does not take long for the economy to receive a blow. In addition, the control of monetary policies by France, as well as the use of the colonial currency, do not leave enough room for an efficient use of BRVM by WAEMU.

This study sheds more light on BRVM, which has not been the subject of extensive research. Diouf and Boutin-Dufresne (2012) focused on WAEMU's growth financing from the securities market and reviewed its achievements and prospects. Ouedraogo and Drabo (2019) have investigated WAEMU's regional integration and economic growth, and Zoungrana et al. (2021) have studied the effect of the occurrence of COVID-19 on BRVM stock returns. Other researchers have also conducted some research on WAEMU or BRVM, but none have focused on the relationship between the two. The relationship between financial market development and national economic growth has been widely studied around the world, and this study is the first of its kind. It provides a survey of the BRVM and economic growth in WAEMU countries under the pressure of a colonial currency.

Another contribution of this paper is that the financial markets considered as a whole, and some of them specifically considered (the stock exchange in this study), show a positive impact on the WAEMU. It also supports the stock and financial market supply leading hypothesis and, primarily, the stock exchange demand-driven hypothesis in WAEMU. Current research results are also consistent with most of the results of previous studies on the causal relationship between stock exchange development and the real economy in low- and middle-income countries (Kolapo and Adaramola 2012; Demirguc-Kunt et al. 2012; Ikikii and Nzomoi 2013; Mittal 2014; Milka 2021; Maku 2020; etc.).

A limitation may be that empirical analysis is not country specific. Proven country interconnections suggest that the economic events of one country are shared with others, but the findings relate to WAEMU as a whole. Therefore, further research may cause similar assessments at the WAEMU-country level. A future study can also focus on how financial debts, especially bonds, affect the economic growth of WAEMU member countries. Moreover, given the growing complaint that the FCFA as a currency slows the development of many African countries, future studies could analyse its role as a vector reducing the performance of the BRVM and the extent to which it hinders the economic prosperity of WAEMU countries. From a governance point of view, later research can examine to which extent policy makers can influence the development of both BRVM and WAEMU countries.

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Data Availability Statement: The datasets used and analyzed in this study are available from the corresponding author on justified request.

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Appendix A

Table A1. Summary statistics.

Variables	Observations	Mean	Median	Std. Dev.	Min.	Max.
Growth	216	3.645	3.932	4.248	−4.666	14.377
SMC	216	1.930	1.478	1.496	0.049	4.728
STTV	216	0.053	0.029	0.048	0.006	0.168
SMTR	216	0.619	0.320	0.976	0.093	4.111
FMA	216	0.003	0.000	0.005	0.000	0.022
FMD	216	0.042	0.012	0.074	0.000	0.256
FD	216	0.106	0.110	0.030	0.013	0.171
CC	216	−0.433	−0.422	0.440	−1.326	0.059
OP	216	0.391	0.000	0.531	0.000	1.680
INV	216	0.039	0.000	0.899	−2.651	3.382
FDI	216	−1.289	−0.933	2.391	−9.913	6.666
PSE	216	66.698	69.793	33.837	0.000	128.736
INF	216	6.930	3.108	14.068	−5.816	67.894

Note: Table of the descriptive statistics for the variables. The sample contains 216-year observations from 1989 to 2015.

Table A2. Cross-sectional independence and slope homogeneity test.

Form	Test	p-Value
Cross-sectional dependence test [a]		
LM Breusch-Pagan test	41.50	0.048
Slope homogeneity test [b]		
$\widetilde{\Delta}$	−0.819	0.413
$\widetilde{\Delta}_{adj}$	−1.181	0.238

Note: The null hypothesis (Ho) for [a] is that there is cross-section independence. For [b], the coefficients are homogeneous.

Table A3. Stationarity test.

Form	Variables	Hadri	LLC	IPS	Fisher-ADF	Conclusion
Normal	Growth	0.1196	0.0000	0.0000	<0.0500	Stationary
	SMC	0.0000	0.4570	0.9995	>0.0500	Non-stationary
	STTV	0.0000	0.7907	1.0000	>0.0500	Non-stationary
	SMTR	0.0494	0.0000	0.0003	<0.0500	Stationary
	FMA	0.0000	1.0000	0.0000	<0.0500	Non-stationary
	FMD	0.0000	0.0583	0.0000	>0.0500	Non-stationary
	FD	0.0000	0.0109	0.0385	<0.0500	Stationary
	CC	0.0000	0.2942	0.0008	<0.0500	Non-stationary
	OP	0.5493	0.3446	0.0000	<0.0500	Stationary
	INV	0.0000	0.8145	0.0000	<0.0500	Non-stationary
	FDI	0.0000	0.0150	0.0016	<0.0500	Stationary
	PSE	0.0000	0.1695	0.2006	<0.0500	Non-stationary
	INF	0.0000	0.0000	0.0000	<0.0500	Stationary
First difference	SMC	0.9303	0.0000	0.0000	<0.0500	Stationary
	STTV	0.3034	0.0000	0.0000	<0.0500	Stationary
	FMA	0.9500	0.0000	0.0000	>0.0500	Stationary
	FMD	0.7796	0.0000	0.0000	<0.0500	Stationary
	CC	0.9957	0.0000	0.0000	<0.0500	Stationary
	INV	0.9885	0.0000	0.0000	<0.0500	Stationary
	PSE	0.9957	0.0000	0.0000	<0.0500	Stationary

Note: For Hadri Lagrange (Hadri), Ho: all the panels are stationary; the alternative hypothesis (Ha) is that some panels contain unit roots. For Levin Lin Chu (LLC), Ho: there are unit roots in the panels, Ha: the panels are stationary. For Im-Pesaran-Shin (IPS), Ho: there are unit roots in all panels, Ha: some panels are stationary. For Fisher, Ho: all the panels contain unit roots, Ha: at least one panel is stationary.

Table A4. Cointegration test.

Form	Test	Statistic	*p*-Value	Conclusion
Kao	Modified Dickey-Fuller	−6.8663	0.0000	Cointegrated
	Dickey-Fuller	−8.5123	0.0000	Cointegrated
	Augmented Dickey-Fuller	−6.0538	0.0000	Cointegrated
	Unadjusted modified Dickey-Fuller	−17.1662	0.0000	Cointegrated
	Unadjusted Dickey-Fuller	−11.0471	0.0000	Cointegrated
Pedroni	Modified Phillips-Perron	0.6275	0.2652	Not Cointegrated
	Phillips-Perron	−6.6608	0.0000	Cointegrated
	Augmented Dickey-Fuller	−7.0636	0.0000	Cointegrated

Note: The tests presented in this table have Ho of no cointegration. Ha is that all panels are cointegrated.

Table A5. Dynamic ordinary least squares (DOLS) regression.

Variables	SMC	STTV	SMTR	FMA	FMD	FD	CC	OP	INV	FDI	PSE	INF	Constant
Coefficients	12.5360	−313.3423	0.6370	708.5800	53.2830	1.2000	15.1240	−0.2080	1.6970	−0.0560	0.0940	−0.0460	3.6000
z-values	(2.66) ***	(−3.00) ***	(1.80) *	(1.76) *	(1.73) *	(1.67) *	(3.17) **	(−0.10)	(1.63) *	(−0.33)	(2.28) **	(−1.84) *	(2.19) **

Note: This table reports the results of the DOLS regression for the cointegrated variables. The z-values are shown in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A6. Causality test.

Variables	SMC	STTV	SMTR	FMA	FMD	FD	CC	OP	INV	FDI	PSE	INF
Test 1												
Coefficients	10.2097	−262.9142	3.5925	1447.8210	69.6771	88.3132	15.6401	−3.9260	−0.4106	−0.4898	−0.0374	−0.1458
z-values	(2.49) **	(−2.21) **	(2.75) ***	(2.87) **	(2.02) **	(2.23) **	(9.67) **	(−2.16) **	(−0.98)	(−2.12) **	(−2.78) **	(−2.96) **
Conclusion	C	C	C	C	C	C	C	C	NC	C	C	C
Test 2												
Coefficients	0.0418	0.0007	−0.0395	0.4843	−0.0484	−0.0009	0.0192	0.6036	−0.0464	−0.0660	1.9810	0.5468
z-values	(3.38) **	(2.29) **	(−2.19) **	(0.28)	(−0.96)	(−5.25) **	(3.49) **	(2.10) *	(−2.79) **	(−2.08) **	(4.12)	(2.95)
Conclusion	C	C	C	NC	NC	C	C	C	C	C	C	C

Note: The test's null hypothesis is that the independent variable does not cause the dependent variable. "C" means causes, and "NC" means does not cause. In test 1, the dependent variable is Growth. In test 2, the direction of causality is reversed, with Growth being the independent variable. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A7. Estimated short-term coefficients for ARDL model.

ARDL Model (1,0,0,0,0,0,4)							
Stock and financial market variables							
Variables	**SMC**	**STTV**	**SMTR**	**FMA**	**FMD**	**FD**	**Constant**
Coefficients	0.0198	11.4781	0.7832	110.5114	8.9475	18.27	1.5005
t-values	(0.03)	(1.66) *	(2.48) **	(0.23)	(0.26)	(0.85)	(1.13)
LM test [a]	Durb. test [b]	Het. test [c]	Norm. [d]	Cusum test	Cus. Sq.	Single test	
1.5010	1.4430	9.9500	49.8200	0.4126 [e]	0.8478 [f]	13.3596 [g]	
(0.2206)	(0.2297)	(0.0016)	(0.0498)				
Control variables							
Variables	**CC**	**OP**	**INV**	**FDI**	**PSE**	**INF**	**Constant**
Coefficients	−2.6005	−0.9851	0.2131	−0.1153	0.0119	−0.0527	3.9363
t-values	(−3.23) ***	(−1.65) *	(0.65)	(−1.91) *	(1.04)	(−1.97)	(6.70) ***
LM test [a]	Durbin test [b]	Het. test [c]	Norm. [d]	Cusum test	Cus. Sq.	Single test	
0.0670	0.0640	30.5400	23.7700	0.3432 [e]	0.5521 [f]	5.6293 [g]	
(0.7964)	(0.8004)	(0.0000)	(0.6430)				

Note: The dependent variable is Growth. [a] Breusch-Godfrey Lagrange Multiplier (LM) test for autocorrelation; the *p*-values is in parentheses. [b] Durbin's alternative test for autocorrelation; the *p*-values is in parentheses. [c] Breusch-Pagan/Cook-Weisberg test for heteroscedasticity; the *p*-values is in parentheses. [d] White test for homoscedasticity; the *p*-values is in parentheses. Cusum, Cusum Square, and Single tests are all for the detection of structural breaks. [e,f] the test statistics are lower than the critical value at 1, 5, and 10%, so we confirm the null hypothesis of no structural break. [g] *p*-values are all > 0.050; thus, we confirm the null hypothesis of no structural break. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A8. Markov-switching dynamic regression.

Variables	SMC	STTV	SMTR	FMA	FMD	FD	CC	OP	INV	FDI	PSE	INF	Constant
Regime 1 (High Volatility),													
Coefficients	−7.7008	280.4843	1.1925	5609.459	−45.0576	181.4329	−12.4264	−9.4715	−1.7978	−1.1427	−0.0501	0.1035	−19.0943
z-values	(−4.22) ***	(2.60) ***	(1.82) *	(3.53) ***	(−0.40)	(3.78) ***	(−4.95) ***	(−5.38) ***	(−1.23)	(−1.73) *	(−1.11)	(0.57)	(−3.24) ***
Regime 2 (Low Volatility),													
Coefficients	0.8345	−0.09028	0.6175	−38.9273	15.4718	−4.1333	0.673	0.2382	0.0535	−0.1035	0.0189	0.0018	3.7029
z-values	(2.12) **	(−1.88) *	(2.71) ***	(−0.12)	(1.69) *	(−0.52)	(1.07)	(0.53)	(0.23)	(−1.17)	(2.31) **	(0.10)	(4.13) ***

Note: The dependent variable is Growth. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

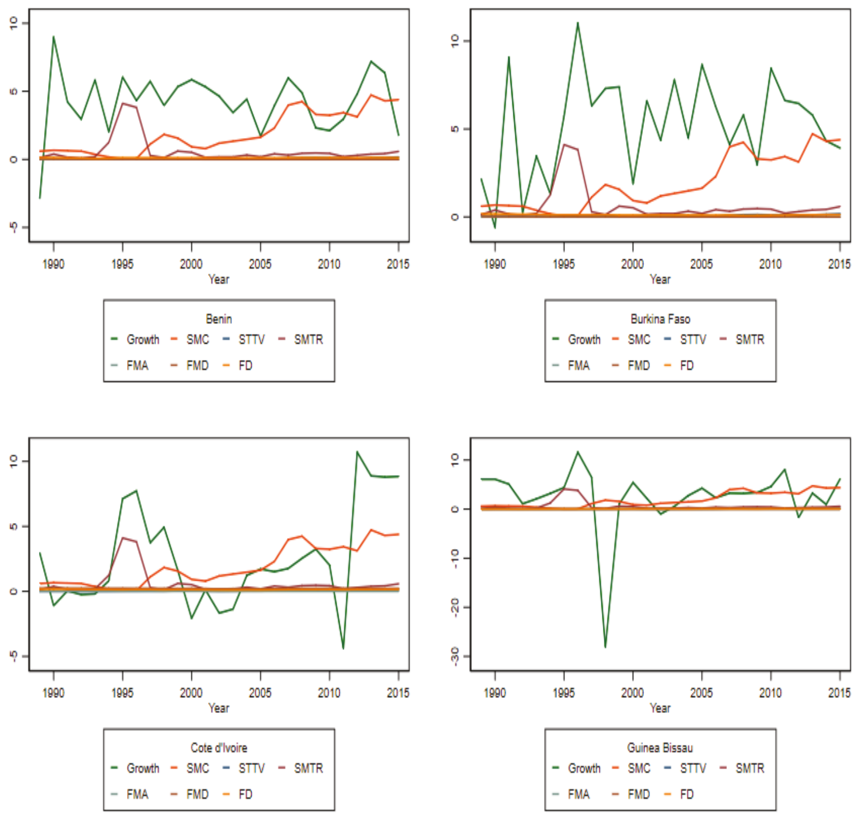

Figure A1. Economic growth and selected stock and financial market variables' evolution from 1989 to 2015 in Benin, Burkina Faso, Cote d'Ivoire, and Guinea Bissau. Source: Prepared by authors, based on collected data.

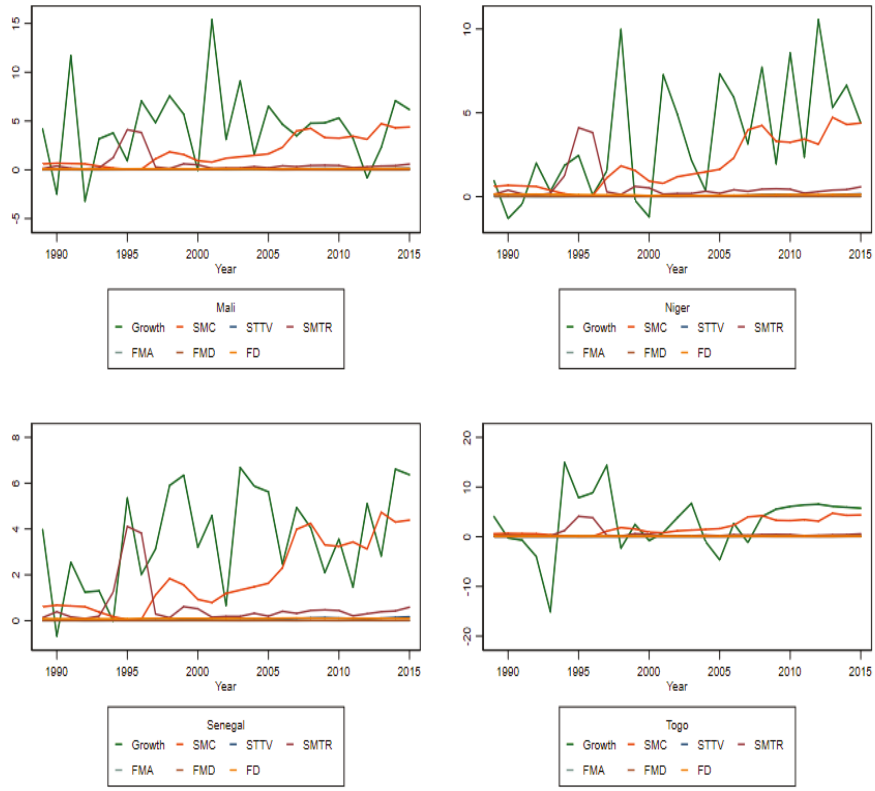

Figure A2. Economic growth and selected stock and financial market variables' evolution from 1989 to 2015 in Mali, Niger, Senegal, and Togo. Source: Prepared by authors, based on collected data.

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Article

What Does Vietnam Gain When Its Currency Depreciates?

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Abstract: The study investigates how the depreciation of the Vietnam dong (VND) against the US dollar (USD) affected export turnover and the stock market in Vietnam during the period from 2000 to 2020. A Markov triple regime-switching model is developed for time-series data involving multistructural breaks. Empirical results reveal that the impact of exchange rates on export turnover and stock price existed both in the long and short run. In the short run, the depreciation of VND led to (i) an increase in export turnover after 12 months; (ii) a decrease in export turnover of the high-growing regime in the short term; (iii) a reduction in stock returns in most cases. In addition, the common cycle from order receipt, preparation, production, and export is about 12 months for all states. The high volatility of export turnover was associated with high export growth. The commonly used phrase of "high risk, high return" seems to not be true for Vietnam's stock market. The results of this study suggest the feasibility of a slight appreciation of VND against USD, which is the key to escape from being labeled a currency manipulator by the US Treasury.

Keywords: currency; export; stock returns; triple regime-switching model; Vietnam

JEL Classification: C22; L85; P44

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1. Introduction

Exchange rates are a hot topic for academic debate and speculative market forces. There are two macroeconomic variables of emerging economies such as Vietnam that play an important role with foreign investors, namely, inflation and exchange rate. The literature *de facto* has not yet paid much attention to studying the advantages and disadvantages of currency devaluation, and its connection to exports and the stock market, which has seen different changes in the implementation of the monetary policy and exchange rates over the past two decades. In particular, the US Department of the Treasury officially labeled Vietnam a currency manipulator at the end of 2020. Being labeled a currency manipulator puts Vietnam at risk of being restricted by the US under US law from accessing procurement contracts, and government and development financing, under US law.

A depreciating currency theoretically supports exports. A weak currency means that domestic goods are cheaper abroad. Therefore, it increases both exports and stock prices, as more businesses raise their capital through the securities market, pushing up the stock price. There is a growing economic literature dealing with the possible effects of exchange rates on exports, such as Sercu and Hulle (1992); Arslan and Wijnbergen (1993); Aristotelous (2001); Hall et al. (2010); Berman et al. (2012); Choudhri and Hakura (2015); Paudel and Burke (2015); Nguyen and Do (2020); Chen et al. (2021). However, there is no clear consensus in the empirical literature on the direction of the relationship, and positive, negative, mixed, or no effects. One of the first studies investigating the interaction between exchange rates and stock prices was conducted by Franck and Young (1972). Numerous articles then successively reported the short- and long-run relationship between them, such as Fang and Loo (1996); Ajayi et al. (1998); Kanas (2000); Homma and Benzion (2005); Phylaktis and Ravazzolo (2005); Hau and Rey (2006); Pan et al. (2007); Caporale et al. (2014); Bahmani-Oskooee and Saha (2015); Reboredo et al. (2016); Sui and Sun (2016); Dahir et al. (2018);

Andriansyah and Messinis (2019); Lee and Brahmasrene (2019); Nguyen et al. (2020); Ding (2021). However, the results and direction of the relationship between exchange rate and stock price are contradictory across studies.

The triple regime-switching model was developed for examining whether the depreciation of the Vietnam dong (VND) to the US dollar (USD) could lead to an increase in future export turnover and stock price in Vietnam. Over the period from 31 July 2000 to 31 December 2020, empirical results show that the depreciation of VND most effectively promotes export growth in a moderate-growth state to which the group of agricultural products, raw materials, and unprocessed goods belong. The high-growth state where the depreciation of VND negatively affects exports should belong to the FDI sector, where export prices do not depend much on the exchange rate in the short term. Meanwhile, the effect on the stock market is generally negative. Empirical results contradict the usual wisdom of "high risk, high return" in the stock market of Vietnam.

This study makes three important contributions to the existing literature. First, as far as it could be ascertained, this is the first study investigating the gain and loss of VND depreciation on export turnover and stock price in Vietnam within asymmetric frameworks. Second, this is one of few studies that take the triple regime model into account for more appropriate results. Third, empirical results suggest that the effect of exchange rates on export and stock price exists both in the long and short run.

These results contribute to the discussion of Vietnam's monetary policy when the US raised the issue of currency manipulation and put Vietnam on the observation list. The remainder of this paper is organized as follows. Section 2 presents a data description. Section 3 outlines the empirical methodology and analysis of the results. Section 4 offers conclusions.

2. Data and Descriptive Statistics

2.1. Data

Data for this study were obtained from two sources. Monthly data of the export value (EXP) and VND/USD exchange rates (EXR) of Vietnam were obtained from the database of the International Monetary Fund (IMF) from 31 July 2000 to 31 December 2020. The monthly data of VN-INDEX (VNI) were taken from Vietstock in the same period.

2.2. Descriptive Statistics

Let EXR, EXP, and VNI denote the vector of exchange rates (EXR), export value (EXP), and VN-INDEX (VNI), respectively. The trends of EXR, EXP, and VNI during the period of 31 July 2000 to 31 December 2020 are plotted in Figure 1. EXP was on an upward trend during the sample period. A significant decrease occurred every February. The VNI was rather stable within the range from 101 to 500 points in the first 5 years since trading commenced on 28 July 2000. In the period from June 2006 to June 2008, Vietnam's index had an unexpectedly strong growth and nearly peaked at 1138 points in March 2007. The 2008 global economic crisis caused the downturn of Vietnam's stock index, which suddenly fell sharply below 300 points in early 2009. Although it was so badly affected by the crisis, VNI quickly recovered after the bleak period, as evidenced by the second half of 2009 to the end of 2020. Vietnam's index maintained continuity and increased, while the exchange rates of VND to USD remained stable except for the drastic increase in the period of April 2008 to February 2011. Table 1 reports the descriptive statistics of EXP, EXR, and VNI, showing that Vietnam's HOSE index reached its maximum at 1174 points in March 2018, export value at USD 27,702.47 million in August 2020, and an exchange rate at VND23,261/USD in May 2020. In addition, skewness and kurtosis show the right-skewed and leptokurtosis of stock return distribution. Jarque–Bera statistics significantly reject the normality of three variables.

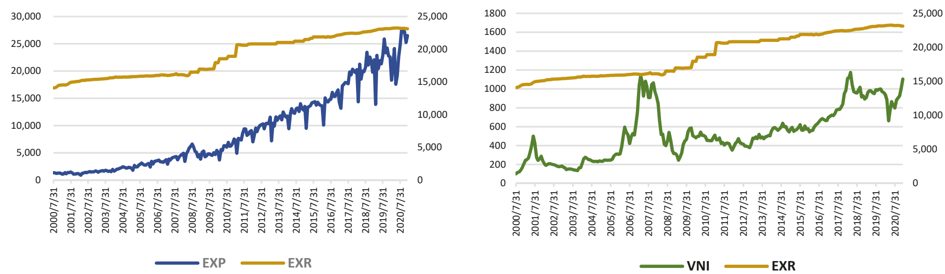

Figure 1. Trend of exchange rate (EXR), export (EXP) and stock index (VNI).

Table 1. Descriptive statistics.

Statistics	EXP	EXR	VNI
Mean	9082.02	18,880.34	533.49
Standard deviation	7287.28	3069.58	273.02
Skewness	0.76	0.02	0.49
Kurtosis	2.43	1.32	2.27
J–B	26.73 ***	28.82 ***	15.21 ***
LB(12)	2402.1 ***	2669.2 ***	1908.9 ***
$LB^2(12)$	1408.9 ***	2253.6 ***	913.61 ***

Note: Sample period spans from July to December 2020. J–B, statistic of Jarque–Bera normal distribution test. Ljung–Box test used for testing for variable autocorrelation. *LB(12)* that uses the lag length of 12 months is the statistics of the Ljung–Box test. $LB^2(12)$ that applies the lag length of 12 months is the Ljung–Box statistics for squared residuals. *** indicates 1% significance level.

Figure 2 shows that, beginning in 2007, the central bank began to loosen the range of effective rates from 0.25% to 0.5%; at the end of 2007, it was further enlarged to 0.75. During this period, the exchange rate regime remained with a small oscillation amplitude. The year 2008 was eventful with many unexpected occurrences for the exchange rate of VND/USD. In the first half of 2008, the central banks applied tightening monetary measures; the interest base rate was adjusted from 8.25% to 8.75%, and inflation was pushed. In the second half of 2008, the rate of VND/USD suddenly increased from 16,600 to 16,998. Then, 2009 was when monetary policy had to face unpredictable challenges arising from the inadequacies of the economy, and the adverse impact of the financial crisis and economic recession. To increase supply and stabilize the foreign exchange market, banks deployed more drastic measures, such as widened exchange rates from +/−3% to +/−5%. Generally, the gap between the average monthly return of stock (0.97%) and the growth of VND/USD (0.20%) was narrow (0.70%). Since the outbreak of the COVID-19 pandemic at the end of January 2020, the US Federal Reserve (FED) has lowered its operating interest rates to 0–0.25% (lower–upper range) and relaunched the quantitative easing (QE) in an effort to rescue the US economy from the pandemic-induced recession. The unprecedented easing policy along with the negative economic growth outlook of the US in 2020 caused the dollar to decline. On 2 November, the dollar strength index fell 2.4% since the beginning of the year. However, as of 30 October, the VND/USD exchange rate has increased slightly by 0.2% compared to the beginning of the year. If investors sell the US dollar (USD) for the Vietnamese dong (VND) to invest in the stock market, their returns adjusted for inflation were negative from July to December 2020, and the gap between the average growth rate of EXP and EXR was about 1%.

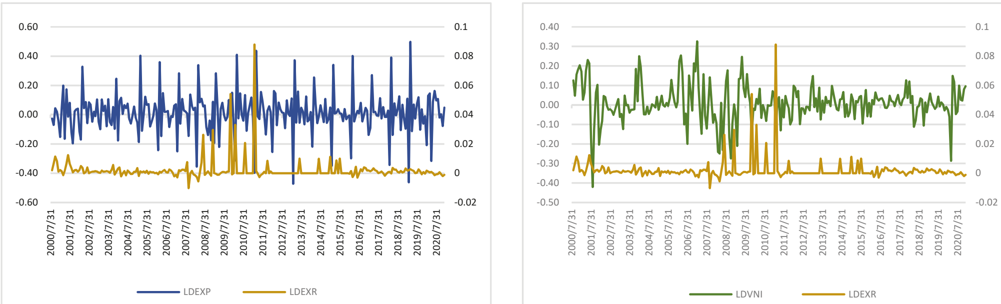

Figure 2. Trend of exchange rate volatility, export growth, and stock returns.

3. Empirical Method and Results

3.1. Empirical Method

The Markov switching dynamic regression (MSDR) of Hamilton (1989), namely, the regime-switching model, is one of the most popular nonlinear time-series models. It involves multiple structures that can characterize the dynamic behaviors of data under different regimes. The basic model with switching intercept is as follows:

$$Y_t = \mu(s_t) + \beta(s_t)X_t + \epsilon_t \tag{1}$$

where

$$\mu = \begin{cases} \mu_1 \, if \; s_t = 1 \; (Regime \; 1) \\ \mu_2 \, if \; s_t = 2 \; (Regime \; 2) \\ \qquad \ldots \\ \mu_n \, if \; s_t = n \; (Regime \; n) \end{cases}$$

Y_t is a dependent variable that follows a process depending on the value of unobserved state s_t. s_t is assumed to have n possible regimes. X_t is a vector of exogenous variables, $\mu(s_t)$ is the conditional mean of Y_t in each specified regime. ϵ_t is an independent and identically distributed (i.i.d.) normal error. The regression model was assumed to be linear in regime n.

The Markov switching regression model extends the basic exogenous probability framework by specifying a first-order Markov process for regime probabilities, where $s_t \in \{0, 1\}$, and regime transitions are calculated according to

$$\mathrm{P}[s_t = a | s_{t-1} = b] = p_{ab}(t) \tag{2}$$

These probabilities are presented in a transition matrix of an ergodic n regimes Markov process as follows:

$$p(t) = \begin{bmatrix} p_{11}(t) & \ldots & p_{1n}(t) \\ \ldots & \ldots & \ldots \\ p_{n1}(t) & \ldots & p_{nn}(t) \end{bmatrix} \tag{3}$$

where element ab represents the probability of transitioning from regime a in period $t-1$ to regime b in period t.

Following Hamilton's (1989), probabilities can be parameterized in terms of a multinomial logit. As each row of the transition matrix specifies a complete set of conditional probabilities, a separate multinomial specification for each row a of the matrix is as follows:

$$p_{ab}(G_{t-1}, \; \vartheta_a) = \frac{\exp\left(G'_{t-1}\vartheta_{ab}\right)}{\sum_{s=1}^{n} \exp\left(G'_{t-1}\vartheta_{ab}\right)} \tag{4}$$

where $a = 1, \ldots, n$, $b = 1, \ldots, n$, $\vartheta_{an} = 0$, and G_{t-1} contains a constant.

The basic switching model can be extended to the Markov switching dynamic regression to allow for dynamics in the form of lagged exogenous variables:

$$Y_t = \mu(s_t) + \sum_{i=1}^{q} \beta_i(s_t)(X_{t-i}) + \sigma(s_t)\epsilon_t \quad (5)$$

where ϵ_t is iid standard normally distributed, and standard deviation $\sigma(s_t)$ is regime-dependent.

For testing the relationship between variables, the autoregressive AR(p) process was added to the model for capturing the remained autocorrelation of residuals:

$$Y_t = \mu(s_t) + \sum_{i=1}^{q} \beta_i(s_t)(X_{t-i}) + \sigma(s_t)\epsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-i} \quad (6)$$

3.2. Empirical Results

Let Y_t denote the vector of EXP, EXR, and VNI. Then, Y_t yields the annual growth rates after taking the differences of its logs:

$$g_t = \log(Y_t) - \log(Y_{t-1}) \quad (7)$$

The Markov switching dynamic regression discussed in the preceding section is only suitable for stationary data. The growth rates of EXP, EXR, and VNI are plotted in Figure 2. These three series were stationary after taking the differences in their log. Results of ADF and DF-GLS unit root tests are reported in Table 2. The equations of unit root tests include both a constant and a time trend. The optimal lag length was selected according to the minimal SIC. Testing results showed that three variables were stationary after taking differences in their log.

Table 2. Unit root tests.

Variable	ADF		DF-GLS	
	Test Statistic	**Lag Length**	**Test Statistic**	**Lag Length**
Level				
Ln_EXP	−1.308	(12)	−1.565	(11)
Ln_EXR	−1.169	(0)	−1.277	(0)
Ln_VNI	−3.433 **	(1)	−2.384	(1)
First difference				
ΔLn_EXP	−6.309 ***	(11)	−2.688 *	(12)
ΔLn_EXR	−15.801 ***	(0)	−15.819 ***	(0)
ΔLn_VNI	−10.853 ***	(0)	−4.829 ***	(3)

Note: Constant and time trend included in all test equations. Maximal lag length applied for the test is 15 periods. Numbers in parentheses are the adequate lag order of the ADF test and DF-GLS test, determined by the minimal SIC. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively. Critical values of ADF derived from Mackinnon (1996). Critical values of DF-GLS derived from Elliott–Rothenberg–Stock (1996).

The residual-based cointegration test of Engle and Granger (1987) was applied for testing the linear and nonlinear long-run effect of EXR on EXP and VNI. Table 3 summarizes the results of the residual-based cointegration test. Both the Engle–Granger tau statistic (t-statistic) and the normalized autocorrelation coefficient (z-statistic) are uniformly failing to reject the null of no cointegration at conventional levels. These test statistics suggest that it is unable to reject the null hypothesis of no cointegration between variables in both linear and nonlinear models. In other words, the long-term influences of the exchange rate on exports and stock index clearly exist.

Table 3. Engle–Granger test for cointegration.

Direction	Linear Model		Nonlinear Model	
	t-Statistic	z-Statistic	t-Statistic	z-Statistic
Ln_EXR → Ln_EXP	−1.6251 (0.896)	−6.059 (0.883)	−1.503 (0.977)	−5.201 (0.983)
Ln_EXR → Ln_VNI	−1.945 (0.795)	−7.876 (0.784)	−2.082 (0.889)	−8.763 (0.899)

Note: Long-run influence of Ln_EXR (exchange rate) on Ln_EXP (export) and Ln_VNI (stock index) examined on the basis of residual-based cointegration test of Engle and Granger (1987). Maximal applied lag was 15 periods. Optimal lag selected according to SIC. Numbers in parentheses are P values (see MacKinnon (1996) for reference).

The Markov switching dynamic regression shows different dynamics across unobserved regimes using regime-related parameters to adapt to structural breaks or other multistate phenomena. To determine the number of regimes for the MSDR model, the structural break test of Bai–Perron (1998) was applied. This method detects the breakpoints of the relationship between Ln_EXP vs. Ln_EXR and Ln_VNI vs. Ln_EXR. As Table 4 shows, two breakpoints were detected for both equations. In other words, the MSDR model with three states was appropriate for examining the nonlinear dynamic effect of EXR on EXP and VNI. The three states represent low-, moderate-, and high-growth states.

Table 4. Structural breakpoint test.

	Ln_EXP vs. Ln_EXR			Ln_VNI vs. Ln_EXR		
Breakpoints	Timepoint	F Value		Timepoint	F Value	
≤1	June 2005	93.371	***	February 2006	73.492	***
≤2	May 2012	68.791	***	January 2013	82.922	***
≤3		1.154			0.000	

Note: Bai–Perron test (1998) applied for detecting breakpoints of the relationship between Ln_EXP vs. Ln_EXR, and Ln_VNI vs. Ln_EXR. F values reject nulls of 0, 1, and 2 breakpoints, but test of 3rd breakpoint did not reject the null. Timepoints of breaks are the first date of the subsequent regime; ***, 1% significance level.

Markov switching dynamic regression was applied to Model 6 using the observations of the whole sample. Estimation results summarized in Tables 5 and 6 were obtained by applying multivariate Markov switching dynamic regression to the after-change sample. p_{11} is the estimated probability of staying in Regime 1 in the next period, and p_{22} is the probability of staying in Regime 2. The estimated standard deviations for the entire process are represented by Log(σ), which shows periods of high and low volatility.

Parameters in Table 5 and smoothing probabilities in Figure 3 characterize the influence of exchange rate on export growth in a given month earlier. Table 5 presents the estimation for five selected periods of exchange rate: same period, 3 months, six months, one year, and two years earlier. As reported in Table 5, μ denotes the mean of three regimes: Regime 1 is the high growth state of export (mean of 4.3%), Regime 2 is the moderate growth state (mean of 0.5%), and Regime 3 is the low growth state (mean of −1.6%). The transition probabilities for Regime 1 to 1 and Regime 2 to 2 are p_{11} and p_{22}, respectively. Both p_{11} and p_{22} showed that the three regimes were highly persistent. The implied standard deviations of Log(σ) are 0.163, 0.059, and 0.003, respectively, indicating that Regime 1 corresponds to the high-volatility period, Regime 2 corresponds to the medium-volatility period, and Regime 3 corresponds to the low-volatility period. Exchange rate volatility had positive and statistically significant impact on export in all three regimes.

Table 5. Effect of exchange rate on export growth.

Variable	Regime 1 (High-Growth Period)		Regime 2 (Moderate-Growth Period)		Regime 3 (Low-Growth Period)	
μ	0.043	***	0.005	*	−0.016	***
	[0.005]		[0.003]		[0.001]	
ΔEXR_t	−2.591	*	1.237		0.197	**
	[1.439]		[0.791]		[0.085]	
ΔEXR_{t-3}	−1.694		2.222	***	−27.745	***
	[1.454]		[0.534]		[0.441]	
ΔEXR_{t-6}	−3.831	***	0.616		−1.471	***
	[0.156]		[0.466]		[0.191]	
ΔEXR_{t-12}	1.530	***	1.691	***	1.922	***
	[0.313]		[0.422]		[0.126]	
ΔEXR_{t-24}	−3.480		2.211	***	0.437	
	[1.316]	***	[0.124]		[0.340]	
$Log(\sigma)$	−1.814	***	−2.826	***	−5.872	***
	[0.097]		[0.104]		[0.265]	
Average duration	4.426		4.497		1.375	
φ_1	−0.543	***				
φ_2	−0.200	***				
p_{11}	2.678	***				
p_{22}	1.589	***				
$Q_{10}\left(uh^{-\frac{1}{2}}\right)$	1.7996	(0.987)				
$Q_{10}\left(u^2h^{-1}\right)$	4.646	(0.914)				
Log L	2144.155					

Note: $Q_{10}\left(uh^{-\frac{1}{2}}\right)$ and $Q_{10}\left(u^2h^{-1}\right)$ represent 10th standardized residual and squared standardized residual of Ljung–Box statistic, respectively. p_{11} and p_{22} stand for Markov transition probabilities. Log L is the value of maximum likelihood function. Values inside square brackes are standard errors. Values inside parentheses are p statistics. *, ** and *** represent 10%, 5% and 1% significant level, respectively.

Results show that the significant signs of coefficients on the lagged exchange rate were not consistent in the three regimes. The depreciation of VND against the USD one year earlier positively affected export growth in all three regimes. These positive effects existed in all cases of Regime 2, where the influence of VND depreciation in three months and two years earlier on export growth was positive and significant. Regime 2 might be the group of agricultural products, raw materials, and unprocessed goods. The depreciation of VND most effectively promotes export growth in a moderate growth state and in one year earlier for all regimes. However, it has the opposite effect in most of the remaining cases of Regimes 1 and 3. Regime 1 where the devaluation of VND negatively affects export should belong to the FDI sector as their export prices do not depend much on the devaluation of VND in the short term. This sector greatly contributed in increasing Vietnam's export capacity and accounts for over 70% of the total export turnover of the country.

Table 6 shows that Regime 1 belongs to the low-return state and has a mean of −2.30%; Regime 2 is the moderate-return state that has a mean of 0.04%; Regime 3 is the high-return state that has a mean of 1.50%. The estimates of p_{11} and p_{22} imply that the three regimes are highly significant.

Results indicate that the depreciation of VND against the USD three months earlier positively and significantly affected stock returns in Regime 2, but it did not in Regimes 1 and 3. Results also indicate that the depreciation of VND negatively and significantly affected stock returns in Regime 3 when stock returns were high.

Table 6. Effect of exchange rate growth on stock returns.

Variable	Regime 1 (Low-Return Period)		Regime 2 (Medium-Return Period)		Regime 3 (High-Return Period)	
μ	−0.023		0.004		0.015	
	[0.032]		[0.006]		[0.009]	
ΔEXR_t	−2.265		1.912		−1.693	***
	[3.919]		[1.528]		[0.606]	
ΔEXR_{t-3}	4.673		4.019	***	−1.030	*
	[3.966]		[1.303]		[0.615]	
ΔEXR_{t-6}	5.748		−3.934	***	0.291	
	[5.645]		[0.796]		[0.699]	
ΔEXR_{t-12}	16.615	*	−1.532	**	0.623	
	[9.142]		[7.649]		[0.651]	
ΔEXR_{t-24}	24.206	*	−0.324		−0.656	
	[13.596]		[0.676]		[0.605]	
Log(σ)	−1.994	***	−3.780	***	−2.817	***
	[0.110]		[0.123]		[0.094]	
Average duration	16.244		4.879		6.500	
φ_1	0.192	***				
φ_2	0.057					
p_{11}	2.724	***				
p_{22}	1.588	**				
$Q_{10}\left(uh^{-\frac{1}{2}}\right)$	3.535	(0.896)				
$Q_{10}\left(u^2h^{-1}\right)$	5.988	(0.816)				
Log L	289.299					

Note: $Q_{10}\left(uh^{-\frac{1}{2}}\right)$ and $Q_{10}\left(u^2h^{-1}\right)$ represent the 10th standardized residual and the squared standardized residual of Ljung–Box statistic, respectively. P_{11} and p_{22} stand for Markov transition probabilities. Log L is the value of maximum likelihood function. Values inside square brackets are standard errors. Values inside parentheses are p statistics. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Results show estimates of Log(σ) in the high-, low-, and medium-volatility regimes. Implied standard deviations were 0.136, 0.023, and 0.059, respectively. The commonly used phrase in investment of "high risk, high return" does not hold in the case of Vietnam's stock market, as taking a high risk does not guarantee that relative high returns can be achieved. Regime 1, with high risk and low returns, lasted the longest. The Ljung–Box diagnostic test statistics $Q_{10}\left(uh^{-\frac{1}{2}}\right)$ for the residuals and $Q_{10}\left(u^2h^{-1}\right)$ for the squared residuals indicate that models in Tables 5 and 6 can describe salient features in export growth rates and stock returns.

Figure 3 is the plot of the smoothing probabilities $P(s_t = a|\aleph_T)$ of the triple regime model that explores how exchange rate growth affects export growth and stock returns. The plot of exchange rate effect on export growth (ΔLn_EXR →ΔLn_EXP) shows that both the red vertical dashed lines at June 2005 and May 2012 are in Regime 2. The highest volatility period was 2008–2009, which coincided with the global financial crisis. This high volatility carries high export growth caused by the depreciation of VND one year earlier.

The plot of exchange rate effect on stock returns (ΔLn_EXR →ΔLn_VNI) shows that most of the high variance regime is located in the first half of the sample. The probabilities of one appeared the most in Regime 1 during February 2006 to May 2009, where the red vertical dashed lines signify the first breakpoint identified by the Bai–Perron test (1998) of the stock index in February 2006. That is, the stock is in a state of low return and high volatility. The second breakpoint occurred at January 2013 where Regime 2 is switched to Regime 3, and the stock is in a state of high return.

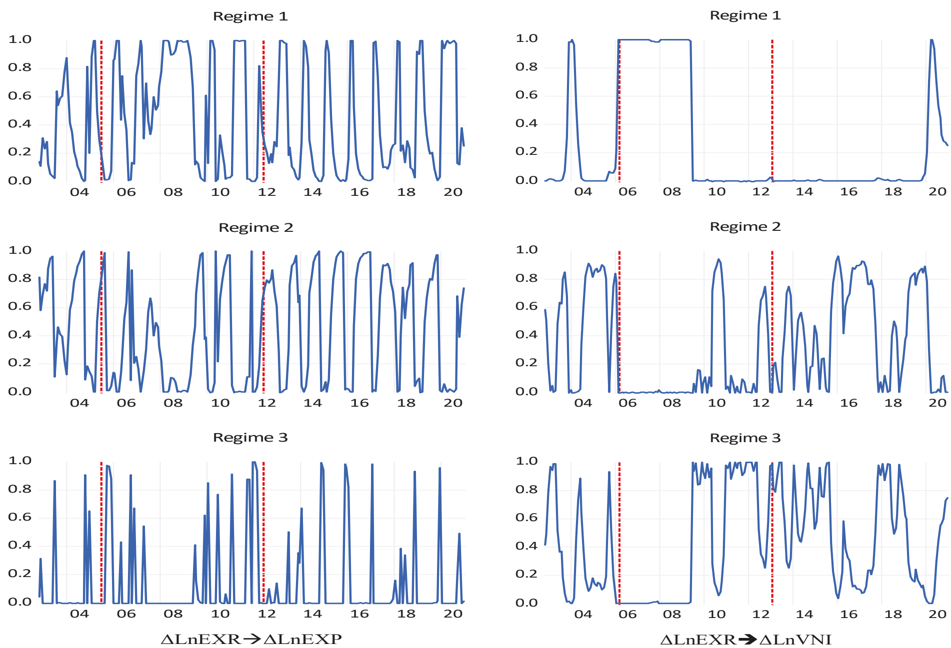

Figure 3. Markov switching smoothed probabilities of triple regime model.

Figure 4 plots the impact of the risk generated by the exchange rates on the export and stock market. It shows that the shock of exchange rates on export is negative, then becomes positive, and slowly diminishes. This implies that the exchange rate first makes the export decrease then slowly rise with a small magnitude, and disappears after 12 months. From the impact on the stock market, it can be found that the effect is not significant and then slowly disappears after 6 months.

To summarize, this study examined the behaviors of exports and stock prices to changes in exchange rates in Vietnam. The VND/USD exchange rate is carefully monitored and controlled by the State Bank of Vietnam (SBV). Generally, the SBV manages the exchange rates to vary within a given range. When exchange rates rise sharply in response to political or economic shocks, the SBV usually intervenes in the market to ensure the stability of the exchange rates. As such, Vietnam's export and stock market may behave differently during different regimes.

The long-term effect of exchanges rates' volatility on the export and stock markets do exist in Vietnam. The signs of these effects are examined with the triple regime-switching model. VND devaluation only significantly increases the export value after 12 months. This shows that the cycle from order receipt, preparation, production, and export is usually 12 months. It also works for most of the periods during the regime of moderate export growth, and it has the opposite effect on the regime of high growth. When considering the combined effect of all 3 regimes, the VND depreciated causes the export value to decrease in the first 2 months; then, it gradually increases but with a narrow range and disappears after 12 months. This implies that, when export products are priced in USD, their prices are lower, causing the export turnover to be lower in the first 2 months, then gradually increasing in the following months on the basis of the devaluation of VND. The devaluation of VND increases stock returns only effectively in the previous 3 months, and this effect only significantly appears in the medium-return period and does not last long. In most remaining cases, the opposite is true. Its combined effect is not significant. Empirical results contradict the usual wisdom of "high risk, high return".

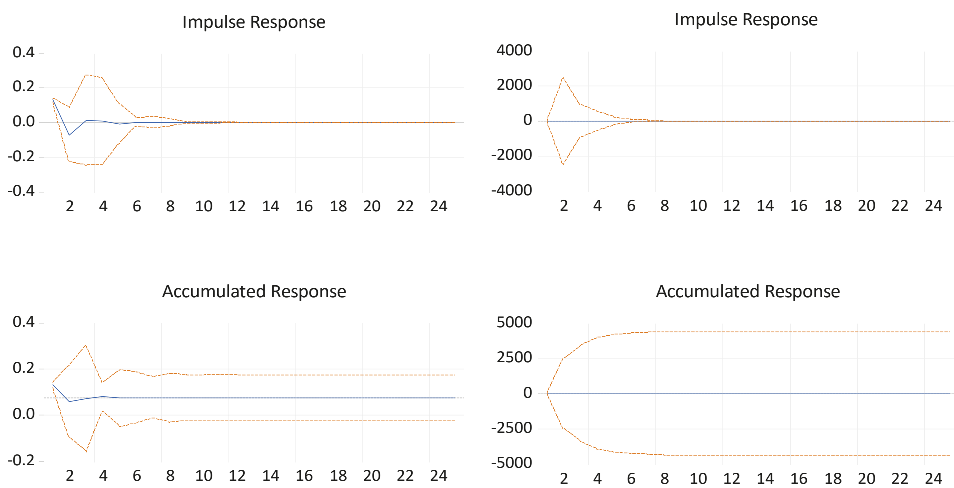

Figure 4. Impulse response of export growth and stock returns to volatility of exchange rate.

4. Conclusions

This study developed a triple regime-switching model in which low-, medium-, and high-growth regimes play roles in explaining a substantially detailed relationship between exchange rates, and export turnover and stock returns. The proposed model allows for multistate phenomena to better capture the time-varying aspect of the effect of exchange rates. Applications of the proposed model on the effect of exchange rates suggest that the depreciation of VND most effectively promotes export growth in a moderate-growth state to which the group of agricultural products, raw materials, and unprocessed goods belong. The high-growth state where the depreciation of VND negatively affects exports should belong to the FDI sector where export prices do not depend much on the exchange rate in the short term. Meanwhile, the effect on the stock market is generally negative. Empirical results contradict the usual wisdom of "high risk, high return" in the stock market of Vietnam.

In the context that the USD is depreciating sharply compared to other currencies in the world, the slight appreciation of VND against USD not only does not harm the competitiveness of export businesses, but could also stimulate investment capital flow into Vietnam, reduce the burden of foreign debt payment, lower the trade imbalance between the US and Vietnam, and be the key to escaping from being labeled a currency manipulator by the US Treasury. This policy adjustment of the State Bank is necessary.

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Dynamic Linkages among Saudi Market Sectors Indices

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Abstract: This study aims to test the causal relationship between Saudi stock market index (TASI) and sectoral indices throughout the period from 2016–2020. The study data were extracted through the main index of the Saudi market and the indices of the available data of 19 sectors out of 21 sectors. The unit root test was used along with the Granger causality test, in addition to multiple regression tests in order to analyze the study hypotheses. The study shows that all index series were stationary at the zero level I (0), and the results also show that there were bidirectional and unidirectional causal relationships between TASI and sectoral indices, and that TASI effectively mirrors all the changes that occur in the Saudi stock market.

Keywords: TASI; unit root; granger causality; sectoral indices

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1. Introduction

In developed and emerging economies, a stock market is one of the fundamental pillars playing active roles in that development, for it acts as an intermediary between borrowers and lenders. An efficient stock market refers to how successful a market is in incorporating stock prices, which reflect the stock value (Keane 1983). This market may accelerate the development process in an economy through raising savings and efficient allocation of resources.

Throughout recent years, stock market integration has become a major topic in finance literature and has gained wide currency due to its high significance for many parties involved (Youcef and Adewale 2017). This integration could generate considerable economic growth across the economy, enhance the allocation of capital, decrease costs of capital, and raise the risk sharing efficiency.

On the contrary, Rehman and Hazazi (2014) explain that this co-movement among economies may increase homogeneity in market performance in reaction to international financial impacts. This might cause a peril from some events such as a credit crunch, capital flight, a contagion effect, and so on.

Accordingly, the transmission of volatility and crises among different sectors of a stock market is an important issue for policy makers, investors and researchers (Mohammed et al. 2020; Ahmed 2016).

There is a significant concern with studies considering the relationship between the general stock market index and the sector indices. For example, Sharabati et al. (2013) and Aravind (2017) illustrate that there is a strong tendency for stock prices to move in accordance with the overall stock market and in parallel with the direction of other stocks in the same sector. Besides, the movement of stock prices in one sector may affect stock prices in another sector. Whenever a company has a large market capitalization, many changes might occur in other stock prices in the same sector (Sharabati et al. 2013). Thus, understanding and examining the relationship between various sectors' indices on one hand and the general index on the other would greatly benefit all parties involved.

Over the last three decades, emerging markets have raised profits enormously, for they provide many investment opportunities in financial sectors (Rehman and Hazazi 2014).

Saudi Arabia, which is considered as the biggest oil exporter country in the world, has one of the strongest stock markets among the Gulf Council Countries (GCC), the Middle East, and North Africa (MENA) (Mustafa 2012). The Saudi stock market (Tadawul) was formally established in 1984, and it is now one of the leading emerging markets in the Arab world. Then, in 2001, and as a result of the rising of the trading volume in Saudi stock, a new official Saudi stock market index called TASI was established (Tadawul All Share Index) (Tadawul 2019). Additionally, the extant statistic reports of Tadawul (2019) mentioned that the number of companies listed on the stock exchange increased from 163 in 2013 to 199 at the end of 2019, with total market capitalization of US$ 2,406.78 billion.

In this context, through conducting the Granger causality between this market's indices, the investigation on the Saudi Arabia's stock market (Tadawul) would contribute to clarifying the volatility of Tadawul.

2. Study Objectives

This study aims at:

1. Testing the causal relationship between the Saudi market index returns and sectoral indices returns.
2. Measuring the efficiency of the TASI in reflecting all changes in the market; measuring whether the index is designed in a way that reflects changes in the market or not.

3. The Importance of the Study

This study adds new information about a developing market such as the Saudi market, which has proven its worth during the previous years as one of the most important markets globally and in the Middle East, especially as it includes the Aramco company which is considered the largest company in the world in terms of market value. Since the Kingdom of Saudi Arabia is considered one of the Group of Twenty countries (G 20), meaning that it is one of the largest economies in the world, and this makes this study of great importance. Finally, this study is considered important because it is the first study that aims to examine the relationships between the Saudi market index (TASI) and sectoral indices, and through its results, this study attempts to provide a service to investors that helps them make their investment decisions.

4. Literature Review

The co-movement among sectors of the equity exchange and the extent of its impact on the general index of the market have long been the subject of researcher attention. Scholars use different research methods and statistics to analyze and understand this relationship. Many use Pearson's correlation method to investigate the relationship between one sector and others in the market (Rajamohan and Muthukamu 2014) or to investigate the linkage among all industries within a market (Mohanty et al. 2019; Cao et al. 2013). Other researchers employ Granger causality to test the effect of industry indices (Mustafa 2012; Ahmed 2016; Aravind 2017). In addition, some studies use ANOVA to analyze the variation among sectoral indices (Sharabati et al. 2013), while others use Vector Error Correction Model (Arbrlaez et al. 2001;Vardhan et al. 2015). Furthermore, Sharabati et al. (2013) employed Johansen's multivariate cointegration analysis to study the abovementioned correlation.

The findings of these studies share some points and differ in others. For instance, Rajamohan and Muthukamu (2014) examined the relationship between the banking industry index and other sectors in the National Stock Exchange of India and found a direct link between the banking industry and other sectors in the market. This result is consistent with Vardhan et al. (2015), who concluded that the banking industry is a leading industry in the Indian Stock Market. Moreover, some studies dealt with the long/short-term relationship like Mustafa (2012), which investigates the co-movement of the Saudi stock market sub-sectors and their connection with the whole market. Considering this to be a long-term relationship, unlike a short-term relationship, there seems to be a positive correlation among Saudi sub-sectors indices. There is also a long-term causality between the sub-sectors and the market portfolio's movement. Similarity, Ahmed (2016) comes to the same conclusion on the Egyptian Stock Exchange and Arbrlaez et al. (2001) did so in their analysis of the Colombian Stock Exchange. Furthermore, there are several research findings about the significance of this connection that vary by sector. By way of illustration, Mohanty et al. (2019) found that all industries in the Bombay stock Market have a positive influence on the market index, except for health care and telecommunications. The health index has an inverse correlation with all other sectors. Yet, the telecommunications industry is directly correlated with the automotive and health sectoral indices, and it is inversely related to the indices for information technology, banks, fast-moving consumer goods, and oil. Likewise, Aravind (2017) demonstrated a unidirectional linkage among the Indian Stock Exchange index, FMCG and IT. However, the banking industry shows a highly significant correlation to the market index. On the other hand, Sharabati et al. (2013) analyzed the data of the Jordanian Stock Exchange to determine the correlations among sectoral indices and the market overall. They found a remarkable positive correlation among the sectors in the long run, especially in the sectors of finance, industry and services respectively. Another study examined the sectoral behavior of the Chinese Stock Market index and divides it into two periods based on economic conditions (Cao et al. 2013). The first occurs when the market experiences a sharp rise and fall in stock prices and sectoral indices show consistent behavior together. The other takes place when the market is in a normal condition, and the findings vary depending on the industry. Some industries indices show strong linkage to the market portfolio, including financial services, energy, and industrials. Nevertheless, some show a weak linkage to the market, such as telecom, IT, and utilities. In addition, some industries show no linkage to the market, such as health, consumer discretionary, and consumer staples (Cao et al. 2013).

Arbrlaez et al. (2001) found that the co-movement among sectoral indices is becoming more significant over time and suggest that this conclusion could be applicable in other emerging markets. There are some studies that examine not only the relationship between market indicators but also between different market indices. The most recent study on this subject is a study of Joshi et al. (2021), where researchers aimed to examine the degree of interdependence between 22 indices in the American and European regions from 2005 to 2018 by using ADF and a causality test. The results indicate that there is a significant amount of interdependence between stock markets. It was also observed that there is an association between markets. Stoupos and Kiohos (2021) tested, through their studies, the integration between the European area stock markets after the end of 2010 debt crisis. The results revealed that the stock market integration was strong between Germany and EA core member-states, but disparate for the EA periphery. In contrast, there are only indications regarding the EA, Eastern Mediterranean and Baltic stock markets' integration with the DAX-30. And there is the Kapar et al. (2020) study, which is one of the studies that examined the integration of financial markets using data from the Dubai Financial Market Stock Exchange, the Abu Dhabi Stock Exchange and the FTSE Nasdaq Dubai UAE 20 index, by applying a vector error correction model and a permanent–transitory decomposition to the series of prices. The researchers found a long-run equilibrium relationship between the three financial indices, suggesting that UAE stock markets are integrated, and they found that shocks to any of these markets affect the other markets in the long and the short run through the equilibrium condition. Furthermore, Nasser and Hajilee (2016) examined stock market integration among five selected emerging stock markets (Brazil, China, Mexico, Russia and Turkey) and the developed markets of the US, UK and Germany by using monthly data from 2001 to 2014. The results show evidence of the existence of short-run integration among stock markets in emerging countries and developed markets, and the long-run coefficients for stock market returns in all emerging countries showed a significant relationship only with Germany's stock market return. Therefore, our study enriches the preceding literature with an up-to-date time series analysis for the Saudi Stock Exchange

(Tadawul). Moreover, it will appeal to investors and portfolio managers by presenting the effectiveness of portfolio diversification in the Saudi equity market.

5. Research Methodology

5.1. Sample and Data

The study sample consists of daily data for the Saudi Stock Market General Index (TASI: Tadawul All Share Index) and 21 sectoral indices from 2016–2020. The study relies on 19 sectors in order to provide data for the indicators of these sectors, as shown in Table 1.

Table 1. Indices and index symbols.

Index	Index Symbol *	Index	Index Symbol *	Index	Index Symbol *
General Index	TASI	Capital Goods	CG	Energy	EN
Materials	MAT	Commercial and Professional Svc	CandPS	Transportation	TR
Consumer Durables and Apparel	CDandA	Consumer Services	CS	Media and Entertainment	MandE
Retailing	RE	Food and Staples Retailing	FandSR	Food and Beverages	FandB
Health Care Equipment and Svc	HCEandS	Pharma, Biotech and Life Science	PBandLS	Diversified Financials	DF
Insurance	IN	Telecommunication Services	TELE	Utilities	UTILI
Real Estate Mgmt and Dev't	REM	Banks	BNK		

* All the symbols were developed by researchers except for the general index.

5.2. The Study Hypotheses

The hypotheses of the study were formulated according to the questions of the study and its goals in order to test the relations between the study variables.

5.2.1. Hypotheses of the Time-Series Non-Stationarity Test

Hypothesis 1 (H1). *TASI returns are nonstationary or have a unit root.*

Hypothesis 2 (H2). *The sectoral indices returns are nonstationary or have a unit root.*

5.2.2. Hypothesis Testing Causality between TASI and Sectoral Indices

Hypothesis 3 (H3). *TASI returns do not cause sectoral returns.*

Hypothesis 4 (H4). *Sectoral indices returns do not cause TASI returns.*

5.2.3. Hypothesis of the Multiple Regression

Hypothesis 5 (H5). *The sectoral indices have no statistically significant effect on the TASI.*

5.3. Statistical Methods Used in the Study

The following tests were used to examine the hypotheses of the study:

5.3.1. Tests of Nonstationarity (Unit Root Test)

Most of the time series of macroeconomic variables are affected by an instability procedure and the presence of a unit root, and regression on a model that contains nonstationary time series will lead to a spurious skew among the data and cause problems in the analysis (Granger and Newbold 1974). Thus, it is not possible to use t-ratios to determine the effect of one variable on another variable in the event of nonstationarity. This is due to the presence of a trend factor which reflects certain conditions that affect all variables, making them change in the same direction despite the absence of a real relationship among them.

Therefore, most studies assume that the time series used in the analysis are stationary series. The stationarity of the time series means that the mean and variance of the series are stationary over time and that the covariance between two time periods depends on the time differences between those two periods (Lags) and not on the real value of time.

If the time series is stationary in its original form, then it is said to be integrated of the zero order I (0), and if it is nonstationary, the time differences must be taken for it until it becomes stationary. One important condition of the cointegration technique is to prove that the time series used in the cointegration model are integrated in the same order.

The nonstationary hypothesis in time series is usually tested by the Autocorrelation Function (ACF) test and the Unit Root Test, a test that examines the long-term statistical properties of variables.

One of the most important tests examining the unit root is the Augmented Dickey-Fuller (ADF) test (Engle and Granger 1987), which suggests the following equations:

With constant and without trend $\Delta Y_t = \alpha + \delta Y_t - 1 + \mu_t$
With constant and with trend $\Delta Y_t = \alpha + \alpha 1T + \delta Y_t - 1 + \mu_t$
Where Y_t = Index Time Series and = Linear Trend.

The null hypothesis of both ADF tests is that a series is nonstationary; hence, rejection of the unit root hypothesis is necessary to support stationarity.

5.3.2. Granger's Causality Test

Before discussing the causal relationship test for time series, it is worth mentioning that this test shows the short-term relationship, unlike the cointegration relationship test, which shows the long-term relationship. It is also noteworthy that these series are stationary and integrated at the same level. (Granger 1986).

The mathematical equation to measure Granger causality depends on the linear regression model used in the prediction method. Granger's study (Granger 1969) is one of the most important studies demonstrating the concept of causality among variables.

To measure the causal relationship in the short term among the indicators, the following equations were used:

$$Y_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + \mu_{1t}$$
$$X_t = \sum_{i=1}^{n} \lambda_i Y_{t-i} + \sum_{j=1}^{n} \sigma_j X_{t-j} + \mu_{2t}$$

The two equations postulate that the current values, Y_t and X_t, are related to their past values, and vice versa. Unidirectional causality from X_t and Y_t is indicated if the estimated coefficients on the lagged X_t are statistically different from zero as a group (i.e., $\Sigma\beta \neq 0$) and if the set of estimated coefficients on the lagged Y_t are not statistically different from zero if $\Sigma\lambda \neq 0$. The converse is also the case for unidirectional causality from $\underline{Y_t}$ to X_t. Feedback or bilateral causality exists when the sets of X_t and Y_t coefficients are statistically different from zero in the above two regressions (Gujarati and Porter 2009).

5.3.3. Multiple Regression

To test the efficiency of the market index in reflecting the changes that occur in the market, a multiple linear regression (MLR) test was employed, using the ordinary least squares (OLS) method.

6. Results and Discussion

6.1. Descriptive Statistics

Table 2 reveals the descriptive analysis of the indicators, which shows average mean returns, median, standard deviations, skewness, kurtosis, etc. The normal distribution of index returns was also tested through Jarque–Bera test. The table also shows that the highest average return is the sector index return for Media and Entertainment. Moreover, it can be seen through the table that the least-risk index, as measured by standard deviation, was TASI (0.009981), which means that the market's portfolio is well diversified compared to other sectors. When measuring normality of the indices in question, it was found that all indicators had normal distributions, as indicated by the test results. It is clear, too, that the probability values obtained for all return series in Jarque–Bera test were statistically significant at 5 percentage level of significance (p-values 0.00 < 0.05).

Table 2. Descriptive statistics.

Index	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
TASI	0.000238	0.000440	0.054972	0.054422	0.009981	−0.311909	7.151503	732.8700	0.000000
CG	8.86×10^{-5}	-7.69×10^{-5}	0.054716	−0.086279	0.013713	−0.726962	8.244954	1231.842	0.000000
EN	0.000116	0.000578	0.072099	−0.083255	0.014795	−0.714334	7.746601	1021.757	0.000000
MAT	0.000217	0.000296	0.050145	−0.062381	0.010805	−0.349827	7.231947	765.0874	0.000000
CandPS	−0.000144	0.000000	0.055347	−0.069565	0.013649	−0.249655	6.929168	652.3456	0.000000
TR	7.68×10^{-5}	0.000306	0.057756	−0.086615	0.013475	−0.735714	9.039188	1606.651	0.000000
CDandA	−0.000593	-8.68×10^{-5}	0.043514	−0.095023	0.014641	−1.349102	10.09367	2395.221	0.000000
CS	−0.000619	−0.000272	0.066434	−0.091661	0.016478	−0.911762	9.135963	1703.889	0.000000
MandE	0.000757	−0.001718	0.099206	−0.098877	0.029390	0.777676	6.359102	569.8035	0.000000
RE	0.000140	0.000134	0.071843	−0.076269	0.013546	−0.17355	8.446517	1238.560	0.000000
FandSR	0.000343	-1.69×10^{-5}	0.084456	−0.088972	0.015347	0.028389	7.904852	1000.528	0.000000
FandB	-8.69×10^{-5}	−0.000173	0.076047	−0.081846	0.013921	−0.071664	8.906486	1451.554	0.000000
HCEandS	-9.79×10^{-5}	−0.0001	0.069805	−0.081724	0.012846	−0.333837	9.002763	1516.916	0.000000
PBandLS	-8.46×10^{-5}	0.000000	0.086726	−0.102517	0.016015	−0.01494	9.699236	1866.287	0.000000
DF	−0.00059	−0.000437	0.070574	−0.100569	0.013001	−1.078841	13.53953	4812.740	0.000000
IN	5.75×10^{-5}	0.000336	0.072648	−0.081483	0.014091	−0.769165	8.041647	1155.379	0.000000
TELE	0.000326	0.000283	0.053508	−0.070404	0.012824	−0.301258	6.318935	473.1499	0.000000
UTILI	0.000369	0.000000	0.094274	−0.09476	0.015362	−0.061654	8.880617	1438.653	0.000000
REM	−0.000201	−0.000448	0.054568	−0.066644	0.012596	−0.048861	6.186437	422.6086	0.000000
BNK	0.000543	0.000408	0.080170	−0.046349	0.011483	0.207672	7.277784	768.1249	0.000000

6.2. Results of Stationarity Test (Unit Root Test)

Table 3 shows the results of the stationarity test of the indices returns after applying the Augmented Dickey-Fuller test. The results indicate that all indices were stationary with the presence of the constant in the equation and with the presence of the constant and linear trends. Consequently, it can be said that the indices are individually integrated to order zero (I (0)), which means that any of sectoral indices can be used to predict another. Thus, it is possible to reject the null Hypothesis H1, which states that the TASI returns are nonstationary.

Table 3. Result of stationarity test.

Name of the Series	ADF (with Constant) at Level	ADF (with Constant and Trend) at Level
TASI	−26.39654 *	−26.38604 *
CG	−26.80089 *	−26.78981 *
EN	−30.70559 *	−30.73192 *
MAT	−28.29010 *	−28.28174 *
CandPS	−29.03020 *	−29.07163 *
TR	−26.96494 *	−26.96804 *
CDandA	−27.60776 *	−27.63174 *
CS	−27.23331 *	−27.35681 *
MandE	−28.26591 *	−28.25209 *
RE	−25.17888 *	−25.22963 *
FandSR	−28.43957 *	−28.42857 *
FandB	−27.19563 *	−27.18508 *
HCEandS	−26.93679 *	−26.92953 *
PBandLS	−31.84689 *	−31.83352 *
DF	−28.30031 *	−28.31324 *
IN	−27.88356 *	−27.87063 *
TELE	−26.87180 *	−26.88294 *
UTILI	−28.72282 *	−28.71862 *
REM	−26.88922 *	−26.88876 *
BNK	−27.68039 *	−27.67806 *

* Significant at 1%.

6.3. Results of Causality Test

Table 4 indicates that, when applying the Granger causality test, it can be concluded that the general Saudi market index (TASI) affects 10 sectoral indices out of the 19 indices of the study sample. This indicates that the TASI return can be used to predict the returns of the sectoral indices that move along with the movements of the TASI, and those indices are: energy, materials, commercial and Professional svc, consumer durables and apparel, retailing, food and staples retailing, food and beverages, pharma, biotech and life science, insurance, and banks. It can also be noted that there are only two indices whose movements affect TASI, transportation and pharma, biotech and life science. The only index that both affects and is affected by the general index is pharma, biotech and life science. Those results indicate that the null Hypothesis H3 can be rejected, which states that TASI returns do not cause sectoral returns. These results also indicate that the null Hypothesis H4 can be rejected, which states that sectoral index returns do not cause TASI returns.

Table 5 indicates that the most influential index among the rest of the sectoral indices was the transportation sector index, which affects 17 sectors, while the least influential index was the media and entertainment sector index, which affects one sector. Moreover, Table 5 shows that the most affected index is the insurance sector index, which is affected by 16 sectors, and the least affected index is the services sector index, which is affected by only one sector.

These results indicate that we can use some series of index returns to predict the return values of other indices, which supports the assumption that there are investment risks in the financial portfolios and reduces the importance of diversifying financial portfolios.

Table 4. Granger causality test between TASI and sectoral indices.

Null Hypothesis	*F*-Statistics	Hypothesis Testing	Null Hypothesis	*F*-Statistics	Hypothesis Testing	Causality Direction
TASI does not Granger Cause CG	1.89333	H3: Fail to reject	CG does not Granger Cause TASI	0.70508	H4: Fail to reject	TASI←//→CG
TASI does not Granger Cause EN	4.56227 *	H3: Reject	EN does not Granger Cause TASI	0.97897	H4: Fail to reject	TASI→EN
TASI does not Granger Cause MAT	2.46887 ***	H3: Reject	MAT does not Granger Cause TASI	0.9711	H4: Fail to reject	TASI→MAT
TASI does not Granger Cause CandPS	3.08188 **	H3: Reject	CandPS does not Granger Cause TASI	0.44402	H4: Fail to reject	TASI→CandPS
TASI does not Granger Cause TR	0.80063	H3: Fail to reject	TR does not Granger Cause TASI	2.55663 ***	H4: Reject	TASI←TR
TASI does not Granger Cause CDandA	5.13947 *	H3: Reject	CDandA does not Granger Cause TASI	1.8705	H4: Fail to reject	TASI→CDandA
TASI does not Granger Cause CS	2.05215	H3: Fail to reject	CS does not Granger Cause TASI	1.61619	H4: Fail to reject	TASI←//→CS
TASI does not Granger Cause MandE	1.97563	H3: Fail to reject	MandE does not Granger Cause TASI	0.60116	H4: Fail to reject	TASI←//→MandE
TASI does not Granger Cause RE	5.95202 *	H3: Reject	RE does not Granger Cause TASI	0.71494	H4: Fail to reject	TASI→RE
TASI does not Granger Cause FandSR	2.89666 ***	H3: Reject	FandSR does not Granger Cause TASI	1.56497	H4: Fail to reject	TASI→FandSR
TASI does not Granger Cause FandB	7.88997 *	H3: Reject	FandB does not Granger Cause TASI	0.30701	H4: Fail to reject	TASI→FandB
TASI does not Granger Cause HCEandS	0.70316	H3: Fail to reject	HCEandS does not Granger Cause TASI	0.44913	H4: Fail to reject	TASI←//→HCEandS
TASI does not Granger Cause PBandLS	3.65216 **	H3: Reject	PBandLS does not Granger Cause TASI	4.84799 *	H4: Reject	TASI←→PBandLS
TASI does not Granger Cause DF	0.5626	H3: Fail to reject	DF does not Granger Cause TASI	1.50465	H4: Fail to reject	TASI←//→DF
TASI does not Granger Cause IN	10.4520 *	H3: Reject	IN does not Granger Cause TASI	1.1635	H4: Fail to reject	TASI→IN
TASI does not Granger Cause TELE	2.18732	H3: Fail to reject	TELE does not Granger Cause TASI	1.22042	H4: Fail to reject	TASI←//→TELE
TASI does not Granger Cause UTILI	1.2735	H3: Fail to reject	UTILI does not Granger Cause TASI	1.70785	H4: Fail to reject	TASI←//→UTILI
TASI does not Granger Cause REM	1.48586	H3: Fail to reject	REM does not Granger Cause TASI	0.38582	H4: Fail to reject	TASI←//→REM
TASI does not Granger Cause BNK	7.47603 *	H3: Reject	BNK does not Granger Cause TASI	1.82353	H4: Fail to reject	TASI→BNK

* Means that it is significant at 1%, ** means it is significant at 5%, *** means it is significant at 10%. ←→ bidirectional, → unidirectional, ←//→ There is no causal relationship.

Table 5. Granger causality test between sectoral indices.

ID \ D	CG	EN	MAT	CandPS	TR	CDandA	CS	MandE	RE	FandSR	FandB	HCEandS	PBandLS	DF	IN	TELE	UTILI	REM	BNK
CG		0.45648	1.48460	1.64998	0.20995	2.28020	0.98936	1.91771	4.09264 **	3.50111 **	3.47637 **	0.36481	2.63952 ***	0.97308	3.63531 **	1.52603	0.46496	0.73568	3.72477 **
EN	2.22344		0.77036	0.36671	0.56483	3.57709 **	1.49635	1.94669	2.20187	5.89044 *	7.29349 *	2.20773	12.3466 *	3.14709 **	4.77162 *	7.06109 *	1.67844	0.12862	2.41638 ***
MAT	0.34400	2.61606 ***		2.96772 **	0.33173	1.69237	0.18539	1.44074	3.65460 **	0.78193	3.86979 **	0.20991	1.66046	0.04367	5.91230 **	1.08331	0.25988	0.80466	4.79116 *
CandPS	2.63571 ***	6.21266 **	0.30529		1.05096	3.52352 **	0.92465	4.31836 **	1.45887	6.45613 *	4.84766 *	3.80464 **	6.10738 *	2.95547 **	4.59283 *	2.83624 ***	1.14745	0.83214	0.68246
TR	6.85930 **	4.11334 **	3.89399 **	2.96593 **		6.80279 *	2.54104 ***	4.66569 *	3.13750 **	6.87121 *	8.19367 *	3.45834 **	8.31641 *	8.79471 *	8.30147 *	6.37070 *	1.29340	3.52543 **	2.97428 **
CDandA	1.44548	1.28390	2.33748 ***	3.61168 **	0.72483		1.77269	2.06741	4.48125 *	3.40628 **	0.20150	1.62787	2.36935	0.47006	0.88935	2.15193	1.49163	4.04055 **	1.64369
CS	1.80188	1.83436	1.34144	2.08737	1.18200	8.83788 *		6.44778 *	5.46203 *	5.95831 *	4.41416 *	0.85118	5.38185 *	4.10659 **	8.40325 *	1.77064	1.18326	0.58021	5.86402 *
MandE	0.98207	0.39089	0.15299	0.88745	0.13565	1.05041	1.44191		0.88847	0.41594	0.26866	0.07854	2.66989 ***	0.19982	0.22625	1.62249	0.41645	0.64377	0.59019
RE	0.21564	2.94480 **	0.24692	1.50073	3.29758 **	6.09736 *	3.15777 **	6.13611 *		1.39713	2.37637 ***	0.01433	3.64740 **	2.61696 ***	4.27132 *	1.62376	1.04112	1.16724	2.42417 ***
FandSR	0.83146	2.59725 ***	1.16367	0.75006	0.22308	2.85825 **	1.65076	1.87439	0.59243		4.09315 **	0.13374	10.5210 *	0.92592	2.89201 ***	1.72467	2.10163	1.71141	1.09028
FandB	1.06214	0.34784	0.94885	0.08365	0.68059	6.17395 *	0.79957	1.72327	1.55711	1.98911		0.55695	1.97791	1.37333	3.66448 **	0.08803	0.31210	0.56422	3.94860 **
HCEandS	0.25333	3.77782 **	1.35182	3.39390 **	0.98259	2.77296 ***	1.76896	2.25019	1.95755	2.92992 ***	5.11320 *		4.92000 *	0.43509	10.3534 *	0.85278	0.55281	1.15481	2.51041 ***
PBandLS	6.63421 **	1.60110	8.39918 *	4.67038 *	1.85522	9.35345 *	6.17454 **	5.42418 *	4.43352 *	2.90183 **	2.77899 ***	6.88935 *		4.76455 *	13.7341 *	1.55533	0.68682	1.80513	6.45582 *
DF	2.12637	3.09986 **	2.85844 ***	3.40077 **	2.59846 ***	7.42607 *	4.60787 *	5.83965 *	8.24118 *	1.48606	3.35658 **	1.19105	3.16425 **		7.95308 *	1.42417	1.56800	0.80819	2.33067 ***
IN	1.06907	0.18593	0.66827	1.01680	1.07746	0.16887	0.26836	1.08523	4.34243 *	1.93661	1.72000	0.00216	3.32984 **	0.08856		0.62921	0.53832	0.31205	2.57755 ***
TELE	1.42282	2.95246 **	3.76718 **	1.35944	1.25798	2.78023 **	1.80026	0.65979	5.37455 *	4.75656 *	7.78107 *	0.79595	0.90434	1.76622	5.41522 *		0.43629	2.37936 ***	2.04284
UTILI	2.06320	0.65770	3.68882 **	0.11051	1.61043	0.69624	0.85317	0.76639	4.81969 *	5.42037 *	1.06253	2.29335 ***	1.20215	2.48028 ***	5.84022 *	3.99679 **		4.72620 *	1.33282
REM	2.01978	3.25918 **	2.01229	2.67992 ***	1.35442	3.32091 **	1.20972	0.73194	1.78848	3.06527 **	3.10933 **	0.93605	7.11331 *	0.71372	5.98932 *	1.85738	2.57013 ***		1.81019
BNK	2.62057 ***	3.56113 **	0.73719	2.12039	0.27232	3.38551 **	2.08882	2.02444	3.78023 **	1.11034	5.41075 ***	0.30352	1.87292	0.27527	5.70006 *	1.37474	1.86040	1.57502	

* Means that it is significant at 1%, ** means it is significant at 5%, *** means it is significant at 10%.

6.4. Results of Regression Analysis

Table 6 shows the results of multiple linear regression test of TASI on sectoral indices. The results indicate the existence of a statistically significant effect of sectoral indices on TASI, and the model explains 99.75% of the changes in the market value. It was found through the results that all sectoral indices have a positive and statistically significant impact on TASI. This enhances the strength of the model for its adoption as an illustrative model for changes in TASI and indicates that TASI is an index that reflects all changes in TADAWUL.

Table 6. Results of multiple linear regression.

Model	T	Sig.	Collinearity Statistics VIF
(Constant)	−1.983369	0.0476	
CG	7.215750	0.0000	2.057
EN	10.29085	0.0000	1.748
MAT	91.34334	0.0000	2.863
CandPS	2.963960	0.0031	1.652
TR	2.492736	0.0128	2.257
CDandA	2.435842	0.0150	1.725
CS	7.491708	0.0000	1.787
MandE	2.931006	00.0035	1.174
RE	19.53803	0.0000	1.633
FandSR	4.967934	0.0000	1.368
FandB	32.37490	0.0000	1.703
HCEandS	5.563406	0.0000	1.820
PBandLS	3.595438	0.0003	1.431
DF	3.862521	0.0001	1.536
IN	17.60858	0.0000	1.812
TELE	32.44337	0.0000	1.657
UTILI	17.09430	0.0000	1.216
REM	47.40722	0.0000	1.646
BNK	174.2409	0.0000	2.305
F-statistic	Prob (*F*-statistic)	Adjusted *R* Square	
21,670.13	0.0000	0.997584	

7. Conclusions

This study was based on testing the causal relationship between the TASI index of the Saudi stock market and determining whether the TASI is an effective tool for expressing the changes taking place in the market and in market sectors. This study attempted to draw conclusions that may help investors in the Saudi stock market (Tadawul) make efficient decisions about diversifying their investments and support their decisions about diversification efficiency. The Augmented Dickey- Fuller test (ADF) and the Granger causality test were used to test these relationships. The results showed that there is stationarity in these chains. The results also showed that there are bidirectional and unidirectional causal relationships between TASI and the sectoral indices. These results indicate the existence of short-term relationships among the indices comprising the Saudi stock market, and these results also show that there is no benefit of diversification. Moreover, the results of the regression analysis revealed that it is possible to rely on TASI to show the movement of Tadawul. These results confirm that the general index of the Saudi market (TASI) is a clear mirror of the changes taking place in sectors in the market. The results of the study were consistent with past findings (Rajamohan and Muthukamu 2014; Vardhan et al. 2015; Mustafa 2012; Ahmed 2016; Arbrlaez et al. 2001; Aravind 2017; Sharabati et al. 2013). We hope that researchers in the future will apply these techniques to studies of similar markets and compare the results of this study with the results from markets that operate in similar environment and conditions.

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Price Index Modeling and Risk Prediction of Sharia Stocks in Indonesia

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Abstract: This study aimed to predict the JKII (Jakarta Islamic Index) price as a price index of sharia stocks and predict the loss risk. This study uses geometric Brownian motion (GBM) and Value at Risk (VaR; with the Monte Carlo Simulation approach) on the daily closing price of JKII from 1 August 2020–13 August 2021 to predict the price and loss risk of JKII at 16 August 2021–23 August 2021. The findings of this study were very accurate for predicting the JKII price with a MAPE value of 2.03%. Then, using VaR with a Monte Carlo Simulation approach, the loss risk prediction for 16 August 2021 (one-day trading period after 13 August 2021) at the 90%, 95%, and 99% confidence levels was 2.40%, 3.07%, and 4.27%, respectively. Most Indonesian Muslims have financial assets in the form of Islamic investments as they offer higher returns within a relatively short time. The movement of all Islamic stock prices traded on the Indonesian stock market can be seen through the Islamic stock price index, namely the JKII (Jakarta Islamic Index). Therefore, the focus of this study was predicting the price and loss risk of JKII as an index of Islamic stock prices in Indonesia. This study extends the previous literature to determine the prediction of JKII price and the loss risk through GBM and VaR using a Monte Carlo simulation approach.

Keywords: Sharia investment; Jakarta Islamic Index (JKII) price; loss risk; geometric Brownian motion; Value at Risk

JEL Classification: G17; G32; H54

1. Introduction

As the largest Muslim country globally, Islam teaching underlies Indonesian activities to fulfill their necessities of life and prepare for a better future, an investment. According to Chabachib et al. (2019), Pamungkas et al. (2018) and Tandelilin (2017), an investment is a commitment of some funds or other resources used for certain businesses at present, with the intention to obtain profits in the future. Profits gained from an investment can be cash receipts (dividends) or an increased investment value (capital gains) (Lusyana and Sherif 2017). From the perspective of Islam, a good investment is an investment made based on Islamic law, and the activities carried out are not prohibited (haram). Investment based on Islamic law is known as Sharia investment (Alam et al. 2017). In practice, there are two forms of Islamic investment that investors may choose: tangible assets (real assets) and financial assets. In recent years, Islamic investments in financial assets tend to be more attractive to investors in Indonesia than real investment because Sharia investment in financial assets offers many benefits that may be greater than investing in tangible assets without violating Islamic Sharia (Toto et al. 2020).

One type of Sharia investment in financial assets is sharia shares. According to Aldiena and Hanif al Hakim (2019), sharia shares are shares of a company with a line of business that does not conflict with Sharia principles. In Indonesia, Islamic stock trading is centered on the Indonesia Stock Exchange (IDX) as the official capital market recognized by the Indonesian government Rosalyn (2018) with several advantages and the potential for greater profits than investing in tangible assets, Islamic stock investments are increasingly attracting investors in Indonesia. The capitalization value of sharia shares on the Indonesia Stock Exchange increases every year. In 2015, the total market capitalization of sharia shares on the IDX was IDR 1737.23 trillion. Each year, the average increase was 3.955% until 2020, while the market capitalization of sharia shares was IDR 2058.77 trillion (OJK 2021). The price movements of sharia shares traded on IDX Indonesia can be seen through the sharia share price index, namely the Jakarta Islamic Index (JKII). The value of the JKII, in particular, provides investors with the performance of Islamic stocks at a specific time, such as price movements and fluctuations, and profit levels. If the JKII is following a rising trend, the prices of Islamic shares on the IDX increase, and vice versa. In addition, JKII can also be used as a benchmark for stock portfolio performance. To analyze the stock price index, one of the quantitative models used to model and predict the stock price index value is geometric Brownian motion (GBM), a developed model first introduced by Louis Bachelier in the early 1900s to predict stock prices (Islam and Nguyen 2020). In the GBM model, the return value of the stock price index successively in a certain period is mutually independent and normally distributed. In other words, if the return data are not mutually independent and normally distributed, then this model cannot be used for prediction. According to Estember and Maraña (2016), there are two parameters in the GBM model called the volatility and drift parameters, which have constant values.

The consideration of the risk of loss that might occur at any time should be taken into account. Every investor needs to prepare an accurate risk management strategy to anticipate the risk of loss to prevent the investment from having a severe impact (Richter and Wilson 2020). To do so, investors must quantify the possible value of the risk of loss (Jacxsens et al. 2016) using a model, such as Value at Risk (VaR). VaR calculates the prediction of the maximum loss that will occur during a holding period with a level of confidence that can be determined according to the needs of investors (Le 2020). Studies on modeling the JKII price index to predict future prices have been conducted for a few years and it is hypothesized that the current JKII price is a linear combination of the white noise process from the previous periods. Based on this hypothesis, the JKII price was modeled and predicted using the first-order moving average (MA) model. The results showed that the first order of the M.A. model is accurate for the prediction of the JKII price index with a mean square error (MSE) value of 5.267. In January 2013–February 2014, the variance of JKII prices was heteroscedastic. So, applied the Autoregressive Integrated Moving Average-Generalized Autoregressive Model was applied (ARIMA-GARCH). The conditional heteroscedasticity (ARIMA-GARCH) model predicts JKII prices for the March 2014 period. The GARCH modeling begins with ARIMA modeling. Based on the Akaike information criterion (AIC) value, the best ARIMA model was ARIMA (0,1,1) with AIC $-$ 4.94. The modeling continued by forming the GARCH model. The GARCH (2.1) model was chosen as the best model with AIC $-$ 5.30. The prediction results obtained had an error value of 2.1%.

Meanwhile, Hanurowati et al. (2016) used the vector autoregressive exogenous (VARX) model to model the JKII price. The external factors considered to affect the price of JKII are the Indonesia Composite Index (ICI) price and the global price of Brent crude oil. The selected VARX model for modeling was VARX (1,1). The residual of the VARX (1,1) model satisfied the white noise assumption and followed a normal distribution; therefore, the prediction results with the mean absolute percentage error (MAPE) for JKII prediction were very accurate, at 3.63%. During the last ten years, research into the prediction of the risk of loss of the JKII price index in Indonesia has never been carried out, however, it only focuses on certain stocks that are included in the category of sharia shops, such as the research conducted (Faturrahman et al. 2021) on the risk of loss using the JKII price index as an observation variable. By knowing the predicted loss on the JKII price index, the estimated loss of all sharia shares that have been listed on the Jakarta Islamic Index can be identified.

Most previous studies discussed JKII price prediction and modeling based on the correlation between the current price index value and the previous one. Given this reality, this study promoted alternative price prediction and modeling of JKII using the GMB model. This model assumed that the past JKII price index return data were mutually independent and normally distributed. The prediction of the risk of loss of the JKII price index was developed using the Value at Risk (VaR) model with a Monte Carlo simulation approach to obtain an estimated loss of all sharia shares listed on the JKII. The study aimed to analyze the JKII as an Islamic stock price index listed on the Indonesia Stock Exchange. This analysis includes price index predictions and JKII risk loss predictions. So far, no studies have examined this issue. Information about future price movements and the value of the risk of loss is very important for investors and companies listed in the JKII. This information can be used as a reference for investors before deciding to invest. Furthermore, for companies, this information can be used as a reference to improve company performance.

The analysis determined the value of JKII using the GBM model and testing the prediction accuracy using MAPE. After obtaining the predictive value, the predicted value of JKII is used to measure the prediction of losses using the VaR method. The data used are the daily closing price of JKII from 1 August 2020–13 August 2021. The data were obtained through the Yahoo Finance website. The results of this price prediction and risk of loss are expected to be an accurate reference and consideration for investors who will use their funds to invest in Islamic stocks traded on the IDX.

The rest of this paper is divided into four sections: the literature review is outlined in Section 1: Introduction, Section 2: Methodology, Section 3: Result, and Section 4: Conclusions is given in the last section.

2. Methodology

2.1. JKII Price Index Modeling and Prediction Using Geometric Brownian Motion (GBM) Model

GBM is a quantitative model utilizing the return value to model for the prediction of the JKII price index in the coming period (Sonono and Mashele 2015). Before using the GBM model, the return value of the JKII price index had to be determined. On the supposition that S_t and S_{t-1} were the JKII price index at times t and $t-1$, respectively, then, the return value of JKII at time t (denoted by X_t) is obtained through the following equation (Siddikee 2018):

$$X_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{1}$$

After obtaining the return value, a data normality test should be done using several methods, including Kolmogorov–Smirnov, Jarque–Bera, or Anderson–Darling test (Mishra et al. 2019). If the return data followed a normal distribution, the analysis was continued to the next stage; otherwise, it was not continued. According to (Azizah et al. 2020), the GBM model is composed of two parameters, namely the average (μ) and volatility (σ) return. So, after completion of the normality test, the next step was to calculate the values of μ and σ. The equation used to obtain the value of μ was as follows:

$$\mu = \frac{1}{N}\sum_{t=1}^{N} X_t \tag{2}$$

In Equation (2), N is the number of sample data used. The measurement of the value of σ was carried out using the following equation:

$$\sigma = \sqrt{\frac{1}{N}\left(\sum_{t=1}^{N}(X_t - \mu)\right)} \tag{3}$$

In the GBM model, μ and σ are two critical parameters because they build the model used to predict the price index. For the JKII price index recorded on a daily time basis, the GBM model used for price prediction is given in the following equation (Si and Bishi 2020):

$$S_{t+1} = S_t \exp\left(\left(\mu - \frac{1}{2}\sigma^2\right)\Delta t + \sigma\sqrt{\Delta t} Z_{t+1}\right) \tag{4}$$

Information:

S_{t+1}: the price of JKII index at time (t + 1);
S_t: the price of JKII index at time t;
M: the mean of JKII in sample return;
σ: the volatility of JKII in sample return;
σ^2: the variance of JKII in sample return;
Z_{t+1}: Standard Normal distributed numbers for the (t + 1) period;
$i = 1, 2, L$;
L: the maximum period for which will predict the value;
Δt: time change. In this study, since the JKII price index was recorded daily, the value Δt is one time/period change.

2.2. Prediction Accuracy Test

According to (Abidin and Jaffar 2014), MAPE is a commonly used method to evaluate the predicted value by considering the effect of the actual value. The calculation of the MAPE value is as follows:

$$\text{MAPE} = \left(\frac{1}{L}\sum_{t=1}^{L}\left|\frac{S_t - \hat{S}_t}{S_t}\right|\right) \times 100\% \tag{5}$$

Information:

S_t: actual JKII price index at time t;
$\hat{S}_t$: JKII price index prediction at time t.

According to Kim and Kim (2016), a good model is a model that has a high predictive accuracy, which is when the actual value and the predicted value have a small difference in value. The following is the accuracy scale of the prediction results based on the MAPE value obtained presented in Table 1. as follows:

Table 1. MAPE accuracy rating scale.

MAPE Value	Accuracy Scale
<10%	Prediction results are very accurate
11–20%	Prediction results are quite accurate
21–50%	Prediction results are still within reasonable limits
>51%	Prediction results are not accurate

Measurement of risk of loss was performed using the risk measure VaR. According to Trimono and Ispriyanti (2017), VaR is a statistical method to help investors estimate the maximum amount of loss that may occur in a certain period with a level of confidence adjusted to the wishes of the investors. In VaR, several approaches can be used for risk prediction. In this study, the method used was the Monte Carlo simulation approach. According to Bouayed (2016), Monte Carlo simulation can be used if the return data follow a normal distribution. In general, the VaR calculation procedure using the Monte Carlo simulation approach on the JKII price index data was as follows:

1. Determine the parameter value including the mean (μ) and variance (σ^2) of the JKII return;
2. Generating random numbers with normal distribution with parameters μ and σ^2 as much as U (values of μ and σ^2 were obtained from step 1);
3. Calculate the estimated maximum loss at the confidence level ($1-\alpha$). The estimated loss value is the quantile value of α from the random number generated in step 2. The estimated loss value obtained is then denoted by W;
4. Calculate the VaR value for the holding period for r days at the confidence level ($1-\alpha$) using the following equation:

$$\mathrm{VaR}_{1-\alpha}\ (\mathrm{JKII}) = W \times \sqrt{r} \tag{6}$$

5. Repeat step (2) to step (4) m times, thus reflecting various possible VaR values. The results obtained from this step are $\mathrm{VaR}_{1-\alpha}$ (JKII)-1, $\mathrm{VaR}_{1-\alpha}$ (JKII)-2, ..., $\mathrm{VaR}_{1-\alpha}$ (JKII)-m;
6. Calculate the average of the results obtained from step (5) to stabilize the predicted value of VaR, as the VaR value generated in each simulation gives a different value.

2.3. Stages of Analysis

The steps for predicting the JKII price index and predicting the risk of loss using the G.B.M. and VaR models with the Monte Carlo Simulation Approach were as follows:

1. Collect JKII price index data;
2. Divide the JKII price index data into two parts: in-sample and out-sample data;
3. Calculate the return value of JKII for in-sample data;
4. Perform normality test on return in-sample data;
5. Calculate the parameter values of the GBM model, which includes σ and μ are in-sample return data;
6. Modeling and predicting stock prices with the geometric Brownian motion method as much as N. N is a lot of out-sample data;
7. Test prediction accuracy using the MAPE method by comparing the predicted JKII price index with the actual JKII price index on out-sample data;
8. Calculating the Value at Risk using the Monte Carlo simulation approach.

3. Results

This study used 329 secondary daily data of the JKII index price downloaded from FinanceYahoo.com (accessed on 10 October 2021) from 1 August 2020 to 13 August 2021. The following is a summary of the price movement of the JKII index in that period, which is depicted through a time series plot:

Figure 1 shows the time series plot in which the movement pattern of the JKII price index is divided into three periods. First, in the period 1 August 2020–1 November 2020, the JKII price index tended to be stable at IDR 500, meaning, during that period, there was no significant decrease or increase in the movement of Islamic stock prices in Indonesia. In the period 1 November 2020–1 February 2021, the JKII price index increased from IDR 500 to IDR 650. The increase in this period was due to the economic activities of Islamic companies in Indonesia starting to bounce back after previously being constrained by the COVID-19 pandemic that hit Indonesia. After the period 1 February 2021 to 13 August 2021, the movement of the JKII price index was moderately stable, which was in the range of IDR 650–IDR 600.

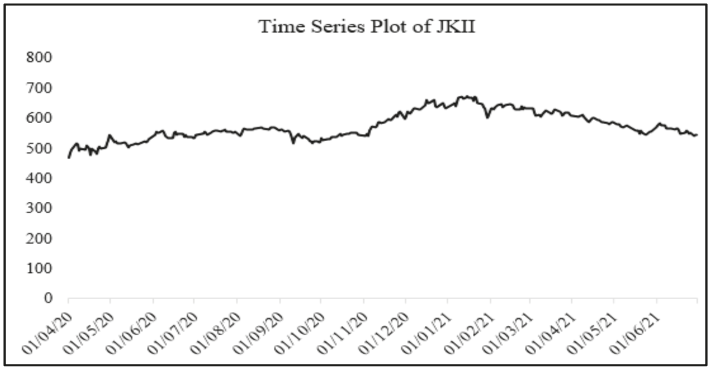

Figure 1. The movement of the JKII price index from 1 August 2020 to 13 August 2021.

According to Aduda et al. (2016), the information presented on the time series plot is limited only to the movement pattern of index price data. Therefore, descriptive statistical values of the JKII price index are needed to obtain more specific information about the characteristics of the JKII price index data.

Table 2 shows that the average JKII price index was IDR 570.45, with the smallest value being IDR 467.88 and the largest being IDR 671.59. The average deviation of the value of each price index to the average value was 44.5246. As this value was relatively small, the value of the JKII price index tended to be homogeneous and stable. The skewness value obtained was 0.4351 > 0, meaning that most of the data had a value less than the average, and on the frequency distribution curve, the data tended to converge on the left side. After determining the characteristics of the JKII price index, the analysis was continued to predict the price index and the value of losses. Prediction of the JKII Price Index began by dividing the data into two: in-sample and out-sample data. In-sample data serve to form model parameters, while out-sample data serve as a comparison to test the accuracy of predictions (Henry et al. 2019). In-sample data were determined to be 299 from 1 August 2020 to 30 June 2021, and out-sample data were 30 from 1 July 2021 to 13 August 2021. After the data were divided into two segments, the next step was to calculate the return value for the in-sample data. The following is a summary of the in-sample returns in the form of a descriptive statistical table:

Table 2. Descriptive statistics of the JKII price index.

Variable	Total Obs	Mean	St. Dev.	Skewness	Kurtosis	Min	Max
JKII	329	570.45	44.5246	0.4351	−0.5970	467.88	671.59

In the in-sample period, the average return was 0.000446, meaning that the average profit from investing in Islamic stocks was 0.446% of the funds invested. The highest profit value obtained was 4.987%, and the highest loss was 5.143% of the invested funds.

In Section 2, it was explained that the assumption that had to be met in predicting the price of the JKII index using the GBM. model was that the return data had to follow the normal distribution. In this study, the normality test was carried out using the Kolmogorov-Smirnov Test (K-S test) and was chosen because this test is an exact test that does not depend on the test's cumulative distribution function. The process carried out is more concise, with accurate results (Luqman et al. 2018). The test output can be seen in the following table:

The provision to reject or accept H_0 in the normality test using the Kolmogorov–Smirnov test is based on the p-value; if the p-value is less than α, then it is decided that H_0 is rejected (Hassani and Silva 2015). Based on Table 3, the p-value was 0.135, which was more significant than α, so the test decision was that the JKII in-sample return data followed a normal distribution. Since the JKII in-sample return data were proved to have a normal distribution, the GBM model could be used to predict the JKII price index.

Table 3. Descriptive statistics of in-sample return of JKII.

Variable	Total Obs	Mean	St. Dev.	Skewness	Kurtosis	Min	Max
In-sample return of JKII	299	0.00045	0.01453	0.04219	1.1848	−0.05143	0.04987

In addition to normality test, it was necessary to perform a unit root test on the JKII in-sample return data. This test aims to see if the data are stationary. If the information is not stationary, the mean and variance are not constant. Thus, the data are not suitable for modeling using GBM, which requires the information to be normally distributed with constant mean and variance. The results of the unit root test using the Augmented Dickey–Fuller (ADF) test are as follows:

The parameters needed in the GBM model are the mean (μ) and daily volatility (σ) of the return data (Nkemnole and Abass 2019). In addition, the volatility value used was the daily volatility because the price index to be predicted was the everyday price index. The following are the values for these two parameters:

By substituting the values of μ and σ in Table 4 into Equation (4), the GBM model for predicting the JKII price index was as follows:

$$\begin{aligned} S_{t+1} &= S_t exp\left(\left(0.000446 - \tfrac{1}{2} \times 0.01453^2\right) \times 1 + 0.01453\sqrt{1}Z_{t+1}\right) \\ &= S_t exp\left(\left(0.000446 - \tfrac{1}{2} \times 0.01453^2\right) + 0.01453\ Z_{t+1}\right) \end{aligned}$$

Table 4. The output of Kolmogorov–Smirnov test for in-sample return of JKII.

Variable	Hypotheses	K-S Value	Sig Level (α)	*p*-Value
In-sample return of JKII	H_0: Return data are normally distributed	1.162	5%	0.135
	H_1: Return data are not normally distributed			

This model was used to predict the JKII price index in the out-sample period (1 July 2021–13 August 2021). The prediction results obtained are shown in Table 5.

Table 5. The output of the ADF test for in-sample return of JKII.

Variable	Hypotheses	t-Statistics	α	*p*-Value
In-sample return of JKII	H_0: Return data are not stationary	−18.985	5%	0.000
	H_1: Return data are stationary			

From the results of the ADF test, the t-statistic value obtained is −18.985 with a *p*-value of 0.000. If the *p*-value is less than α, then H_0 is rejected. So it can be concluded that the return data are stationary. Estimated GBM model parameters are presented in Table 6 as follows:

Table 6. Estimated GBM model parameters.

Variable	Mean (μ)	Volatility (σ)
In-sample return of JKII	0.000446	0.01453

Referring to Table 7, the predicted results of the JKII index and the return had a value that was quite close to the actual value. This indicated that the GBM model was suitable to be used by investors to predict the movement of JKII and sharia stock prices in the future period. Sometimes, prediction results will be easier to understand if presented in tabular form. Therefore, here we offer the plots of the JKII price index and JKII return prediction and Plots of actual. Plots of actual and predicted JKII price in-dex from 1 July 2021–12 August 2021 are presented in Figure 2 and Plots of actual and predicted JKII return from 1 July 2021–12 August 2021 are presented in Figure 3:

Table 7. Prediction results of the JKII price index and the return for the out-sample period (1 July 2021–13 August 2021).

Date	Actual (IDR)		Prediction (IDR)	
	Price Index	Return	Price Index	Return
1 July 2021	549.01	0.0001	543.25	0.0002
2 July 2021	547.52	−0.0027	557.49	0.0259
5 July 2021	539.43	−0.0149	557.14	−0.0006
6 July 2021	549.42	0.0184	566.86	0.0173
7 July 2021	548.81	−0.0011	571.07	0.0074
8 July 2021	543.8	−0.0092	561.52	−0.0169
9 July 2021	549.97	0.0113	550.84	−0.0192
12 July 2021	553.22	0.0059	533.27	−0.0324
13 July 2021	546.71	−0.0118	532.74	−0.001
14 July 2021	544.19	−0.0046	526.15	−0.0124
15 July 2021	547.74	0.0065	526.57	0.0008
16 July 2021	550.79	0.0056	528.97	0.0045
19 July 2021	546.67	−0.0075	535.07	0.0115
21 July 2021	545.28	−0.0025	548.73	0.0252
22 July 2021	552.24	0.0127	538.59	−0.0187
23 July 2021	541.75	−0.0192	538.5	−0.0002
26 July 2021	540.43	−0.0024	536.98	−0.0028
27 July 2021	538.36	−0.0038	528.22	−0.0164
28 July 2021	533.74	−0.0086	524.56	−0.007
29 July 2021	537.87	0.0077	526.88	0.0044
30 July 2021	532.79	−0.0095	528.65	0.0034
2 August 2021	540.81	0.0149	540.73	0.0226
3 August 2021	540.94	0.0002	541.12	0.0007
4 August 2021	543.54	0.0048	529.05	−0.0226
5 August 2021	541.74	−0.0033	524.61	−0.0084
6 August 2021	541.13	−0.0011	516.14	−0.0163
9 August 2021	530.45	−0.0199	526.32	0.0195
10 August 2021	527.5	−0.0056	523.83	−0.0047
12 August 2021	539.83	0.0231	529.44	0.0107
13 August 2021	540.13	0.0006	539.55	0.0189

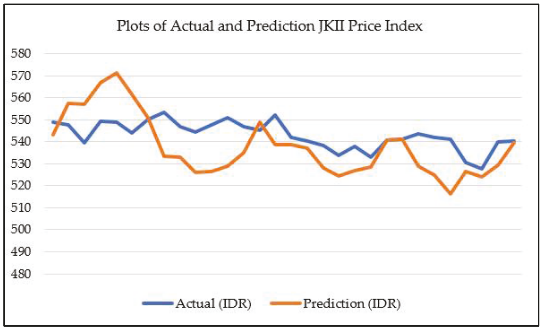

Figure 2. Plots of actual and predicted JKII price index from 1 July 2021–12 August 2021.

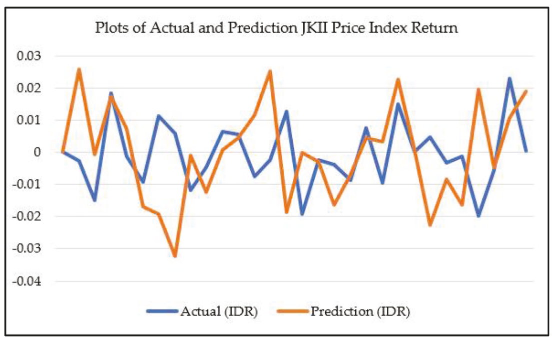

Figure 3. Plots of actual and prediction JKII return from 1 July 2021–12 August 2021.

The following is the MAPE value of the JKII price index prediction for out-sample data.

Based on the obtained MAPE value, the GBM model produced very accurate prediction results, resulting from the return value, which was usually distributed (Ibrahim et al. 2021). Several previous studies applied the GBM. Model to predict prices, and the results showed that if the assumption of normality were met, the prediction would yield very accurate results. Abidin and Jaffar (2014), who used the GBM model to predict stock prices of 22 companies in Malaysia, obtained exact prediction results, with MAPE values ranging from 1.69–10.60%. Trimono and Ispriyanti (2017), who analyzed the share price of Ciputra Development Ltd. in 2016−2017 using the GBM model, produced a very accurate MAPE value of 1.87%. In addition, several other studies examining the application of the GMB model to analyze price movements and predictions concluded that the MAPE obtained was always accurate, at less than 10% (Nkemnole and Abass 2019). After the GBM model was proven to have good predictive accuracy, the model was used to predict the JKII price index for the following five periods after 13 August 2021. The prediction results are presented in Table 8 and Prediction of JKII price index for 16 August 2021–23 August 2021 is presented in Table 9:

Table 8. MAPE value predictions for the JKII price index.

MAPE	Prediction Accuracy
2.03%	Prediction results are very accurate

Table 9. Prediction of JKII price index for 16 August 2021–23 August 2021.

Date	Prediction (IDR)	
	Price Index	Return
16 August 2021	552.26	0.0233
18 August 2021	550.77	−0.0027
19 August 2021	555.22	0.0080
20 August 2021	556.13	0.0016
23 August 2021	545.24	−0.0198

Based on forecasts, the JKII price index would move stably in the following five periods at a price range of IDR 550. The price stability reflected the stable returns to be received. This is a perfect situation for investors who did not like high risk in investing. In addition to the price index prediction, the risk of loss prediction was the next aim of this study. The initial period as the benchmark was 13 August 2021. Through the VaR method with the Monte Carlo simulation approach, the loss risk prediction at several confidence levels and holding periods was predicted. For each simulation to produce the VaR value, the number of random numbers generated was 1000, and the number of repetitions (m) carried out was 500. Loss risk prediction for several holding periods and confidence levels are presented in Table 10:

Table 10. Loss risk prediction for several holding periods and confidence levels.

Holding Period(s)	Confidence Level	VaR Value
1 day	90%	−0.0240
	95%	−0.0307
	99%	−0.0427
3 days	90%	−0.0417
	95%	−0.0529
	99%	−0.0742
5 days	90%	−0.0537
	95%	−0.0684
	99%	−0.0955

In each holding period, a possible loss of value at several levels of confidence might occur. As a negative sign on a VaR value represents a loss value (Maruddani 2019), the interpretation of the VaR value for a 3-day holding period at a 95% confidence level was −0.0529. The meaning was that the maximum possible loss value for Islamic stocks in Indonesia for three trading periods after 13 August 2021, namely on 19 August 2021, was 0.0529 (5.29%) of the total invested funds. In other words, suppose that the invested funds were IDR 100,000,000, then the estimated maximum loss that might occur was IDR 5,290,000. Therefore, the longer the holding period and the greater the level of confidence chosen, the greater the prediction of losses will be. This finding was in line with the previous studies of Amin et al. (2019); Hong et al. (2014), which used the VaR Monte Carlo simulation model to predict losses on financial asset data.

4. Conclusions

In the JKII price index, the GBM model can be used as an alternative to predict the value of the price index in the future. Based on the results of the analysis obtained in Section 4, by utilizing the return value of the JKII price index for the period 1 August

2020–13 August 2021, the GBM model formed to predict the JKII price index with a change in 1 day was:

$$S_{t+1} = S_t exp\left(\left(0.000446 - \frac{1}{2} \times 0.01453^2\right) + 0.01453Z_{t+1}\right)$$

The MAPE value for prediction results on out-sample data (1 July 2021–13 August 2021) is 2.03%; in other words, the prediction results are very accurate. For the period outside of the out-sample data, which was 16 August 2021, the predicted value of the JKII price index was IDR 552.26. Then, through the VaR method with the Monte Carlo simulation approach, at a 95% confidence level, the predicted maximum loss that would occur on 16 August 2021 was 3.07%.

The results of this study indicate that when the return on the JKII price index is normally distributed, then GBM model can predict the JKII price index very accurately. Theoretically, the GBM model will provide maximum predictive results for asset prices when the return data are normally distributed. VaR risk prediction results through the Monte Carlo simulation approach at a confidence level of 90–99% were in the range of 2–9% of the total invested funds. The main difference between the results of this study and other studies that discuss JKII price index prediction is that the predicted results of the price index are directly interpreted as the final result of the study. However, the results of the price index prediction in this study are used as a reference to measure the value of risk of loss, which is also an important indicator of a financial instrument.

The implication of this research is if the return on the sample data are not distributed and price prediction is conducted using the GBM model, the prediction results will be inaccurate and cannot be accounted for. This implication is indirectly at the same time a limitation of this study. GBM and the VaR Monte Carlo model rely heavily on the assumption of normality returns, so that if the return data are not normally distributed, the methods cannot be used. Suggestions for further research can be developed to model the JKII price index if the historical return data are not normally distributed. One of the models that can be used is the GBM with the Jump model.

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Article

Power Theory of Exchange and Money

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Abstract: Modern exchange theories model a large market, but do not explain single exchanges. This paper considers the phenomenon of single exchange and formulates the general exchange problem in the form of a system of two equations, subjective and objective. Subjective equilibrium is given by the Walras–Jevons marginal utility equation. Objective equilibrium equations by Walras and Jevons are averaged over all transactions in the market and can only give a rough general picture without explaining the specific price of an individual exchange. An exchange micro-condition must be found that, when averaged, will give the Walras market equilibrium macro-condition. The study of the internal structure of exchange leads to the need to consider power. The concept of generalized power is introduced. It is generalized power that serves as the primary comparable and measurable objective basis of exchange. The power theory of exchange provides the objective price-equation. It is demonstrated that money is a measure of generalized power in exchange and a certification of generalized power in subsequent exchanges. This methodology is based on an interdisciplinary analysis of an abstract exchange model in the form of a system of equations. The proposed theory is able to uniformly explain any exchange, including a single one, which is impossible with the existing theories of exchange.

Keywords: exchange; exchange theory; money; money theory; power

JEL Classification: A10; A13; A14; D00; D41; D46; D51; E40; G00; Z13

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1. Introduction

Many authors, regardless of their scientific views, assign a key role to exchange in economic research. In Karl Marx's book *Das Kapital*, the second chapter is dedicated exclusively to exchange (Marx 1909). Ludwig von Mises, a representative of a completely different movement and an ideological opponent of Marx's, wrote that "the exchange relation is the fundamental social relation" (Mises 1998). According to William Stanley Jevons: "It is impossible to have a correct idea of the science of Economics without a perfect comprehension of the Theory of Exchange" (Jevons 1924).

Theorists have achieved remarkable results in constructing models of market exchange under conditions where a large volume of transactions are conducted (hereinafter "large market"). However, in the case of a simple discrete exchange, the existing approaches do not provide a complete explanation. The central element of modern economics is the Walrasian general equilibrium model, which is designed for a large market, when supply and demand are generated by many buyers and sellers. However, this model does not explain the case of a simple exchange. At the beginning of his book, Walras mentions that "Of course, our theory should cover all such special cases . . . . Market . . . in which there is a single buyer, a single seller . . . ", but later in the book he deals only with "exchange as it arises under . . . competitive conditions [of the large market]" (Walras 1954). As Alfred Marshall (1890) noted "in a casual bargain that one person makes with another . . . , there is seldom anything that can properly be called an equilibrium of supply and demand". Francis Ysidro Edgeworth (1881) was more defined: "Contract without competition is indeterminate". To obtain an unambiguous solution of exchange problem, these theories refer to the conditions caused by the large market. Franco Donzelli wrote in detail about the role of these conditions in the article "Negishi on Edgeworth on Jevons's law of indifference, Walras's equilibrium, and the role of large numbers: a critical assessment" (Donzelli 2012) so I will not explore the issue in depth here. Instead, I will consider only those aspects that are important for further reasoning. The aim of this paper is to build a complete model that will be able to describe any exchange uniformly, irrespective of whether it occurs on a large market or if it is a one-off event.

Section 3 considers the important role of the large market in existing exchange theories. Section 4 presents the formulation of the exchange problem as a system of two equations with two unknowns. Then, one of the equations is determined. Section 5 examines the concept of power and introduces the concept of generalized power. The application of these concepts in the case of exchange is introduced. Section 6 outlines a power theory of exchange and determines the second equation. Section 7 presents a power theory of money.

2. Methodology

This research is based on the construction of an abstract model of a single exchange, expressed in mathematical form. The explanatory component of the theory is interdisciplinary in nature; it essentially uses concepts from sociology and political science. Analysis of the model allows me to apply these concepts to understand the measurable basis of exchange and the essence of money. Further reasoning allows to determine the position of the proposed theory in the existing modern structure of the exchange theory.

3. Role of the Large Market on Exchange Theories

It is best to start by considering the assumptions of modern exchange theories, which are dependent on the influence of the large market. According to Walrasian exchange theory, prices are determined by the competitive market as a result of supply demand equilibrium. In particular, Walras illustrates his position by the example of trade in wheat: the price "does not result either from the will of the buyer or from the will of the seller or from any agreement between the two" because price is a "natural phenomenon" (Walras 1954). This quote clearly shows the difference between the cases of a simple exchange and a large market, because in a simple exchange, the exchange rate depends precisely on the will of the participants and on their agreement.

Under an alternative approach, the Jevons exchange theory, the additional condition is the "law of indifference", which alone allowed Jevons to construct a system of two equations. He wrote that "the two equations are sufficient to determine the results of exchange; for there are only two unknown quantities concerned, namely, x and y, the quantities given and received" (Jevons 1924). Later, Edgeworth, writing on the Jevons equations, criticized the axiomatic introduction of an additional condition and offered his way of solving the problem through the introduction of "perfect competition," which is in fact the large market (Edgeworth 1881). Despite subsequent attempts by Takashi Negishi to defend Jevons' conclusions (Negishi 1989), they were challenged by Donzelli. Donzelli wrote: "The failure of Negishi's attempt confirms, in the last analysis, that Edgeworth's results cannot be improved . . . stronger results depend on the special assumptions adopted" (Donzelli 2012).

Both Walras and Jevons' models are based on marginal utility theory (MUT), where exchange is viewed through the subjective estimations of the participants. In order to find a solution in each model it was necessary to add objective conditions to the subjective equations of marginal utility. To Walras, this additional condition was the law of one price caused by supply–demand equilibrium on the market. As for Jevons, when analyzing his equations, Edgeworth demonstrated that the incorporation of "perfect competition" with a large number of actors into the model allows one to obtain a single solution. In other words, to solve the problem, Edgeworth was forced to go beyond the only subjective assessment of utility and to introduce an objective factor, perfect competition, which is the result of a social phenomenon, a large market. The necessity of adding objective circumstances to subjective assessments is not accidental, as will be seen later. In addition, it will be emphasized that the mathematical form of the corresponding Walras and Edgeworth–Jevons's price-equations does not depend on the parties involved in the exchange (at the same time, their equations for marginal utility depend on the parties of exchange in an explicit form). These equations set a uniform price for the entire market. However, in reality, even in a large market, the personalities of the participants in the single exchange can influence the price, and in the same market, different prices are possible in different exchanges.

Thus far, I have only focused on the models that are based on MUT. However, there is also another approach, which is based on the labor theory of value (LTV). I will cover it later. I start by considering a simple exchange in general terms.

4. Two Conditions, Two Equations

A simple single exchange is the interaction of two actors (participants, subjects, parties, or commodity owners) whereby negotiation (bargaining) is conducted and the ratio of exchange is defined. After an agreement has been reached, objects (goods) of exchange are transferred mutually in specified amounts. The concept of a transfer will require special attention later.

If two participants H1 and H2 exchange objects O1 and O2, then their common task is to determine the number x of objects O1 and the number y of objects O2 that will be transferred mutually in the course of exchange. Exchange is thus a problem with two unknowns. When they bid, the participants in the exchange are setting the specific values of the variables x and y with a view to solving the problem together.

A twofold interpretation of the factors of the object of exchange has formed gradually since the time of Aristotle. On the one hand, the exchanged items can satisfy human needs, be useful and thus have value for individuals as object of utility. This factor is called use value. On the other hand, objects can be exchanged for other things, and thus they have value for individuals as a means of obtaining other goods. This factor is called exchange value. Both factors have roles to play in exchange and both influence its outcome. Researchers have explained them in different ways. For example, to Marx, the rationale of exchange value is materialized labor. To Walras, it is scarcity. Böhm-Bawerk deeply studied the question of the duality of exchange and use values and especially pointed out that values can be subjective and objective (Böhm-Bawerk 1886).

Exchange value manifests in the interaction between the exchanging parties as a quantitative ratio. It arises as a compromise between the interests of the participants in the exchange. Exchange value is the result of economic interaction between two members of society. This result has an objective basis because when specific values are established during exchange, a decision is made jointly by two participants, each of whom is forced to consider the wishes of the other. In addition, other external circumstances of a social nature may exercise an influence on the ratios of exchange. For example, the presence of a large number of sellers in the market can change the exchange ratio compared to the case when there are no other sellers. Therefore, in the case of exchange value, there is some objective condition of exchange that is established during an interaction between two subjects. If exchange is considered a solution to a problem with two unknowns, then the circumstance of exchange value can be represented in a very general form as a function OB that imposes restrictions on the variables x and y.

$$OB\ (x, y) = 0\text{—the equation of objective equilibrium or price equation.} \tag{1}$$

The OB function is objective in nature, that is, it does not reflect the purely personal assessments of each side but instead arises from the interaction of the parties, and it may depend on social circumstances.

The use value that participants can extract from the objects of exchange is subjective. Participants must take this factor into account when exchanging since everyone seeks to benefit themselves. Thus, use value can be understood as a subjective condition of exchange that each participant estimates for themselves. However, these estimates also affect the exchange and set its conditions. If exchange is construed as a solution to a problem with two unknowns, then the circumstance of use value can be represented in a very general form as a function SU that imposes restrictions on the variables x and y

$$SU\ (x, y) = 0\text{—subjective equilibrium equation or quantity equation.} \tag{2}$$

Thus, two conditions of exchange can be discerned, one that is objective (public) and another that is subjective (personal). Each condition imposes a restriction on the unknown variables. Moreover, by their nature, these conditions are independent: whatever the personal preferences and needs of each subject (condition of the SU), they collide with the opposite interests of the other in the course of bargaining, forcing the two to develop a minimally objective compromise (condition OB).

Mathematically, finding the values of two unknowns requires two independent equations that restrict the two variables. One equation gives the ratio of the variables (price), and the second determines the absolute solution (final amount). Therefore, proceeding from general considerations, one can expect that the participants in the exchange must solve a system of two equations that have already defined before, connecting the variables x and y.

$$\begin{cases} OB(x, y) = 0 \\ SU(x, y) = 0 \end{cases} \tag{3}$$

This system of equations may not have solutions, and then the exchange will not take place.

What are the equations in system (3)? Earlier, I discussed two models of exchange that are based on MUT. These models propose equations that describe the subjective conditions of exchange as they compare the subjective marginal utilities for the parties. Moreover, as Walras showed, the ideologically different models of Jevons and Walras are mathematically identical. Walras wrote that for the case of exchange between two individuals "Jevons's formula is identical with our own, except that he used quantities exchanged where we use prices" (Walras 1954). Therefore, the MUT provides one independent equation for comparing marginal utility in exchange. Consider the Jevons equation in the form given by Edgeworth (1881):

$$\frac{\varphi_1(a-x)}{\psi_1(y)} = \frac{\varphi_2(x)}{\psi_2(b-y)} \tag{4}$$

where φ_1 and ψ_1 denote the marginal utilities of two products for participant H1, and this participant surrenders x units of one product out of a total of a that they hold. In return, they receive y units of another product. The functions φ_2 and ψ_2 have the same meaning for participant H2. Since this equation imposes a condition on the utility ratios for the two participants, I can employ (4) as a subjective equilibrium equation SU (x, y). To maintain consistency with chosen form, I rewrite it as

$$SU(x, y) = \varphi_1(a-x)\psi_2(b-y) - \varphi_2(x)\psi_1(y) = 0. \tag{5}$$

Before continuing, it should be noted that both Walras and Jevons proposed their variants of equations as the first equation OB in this system (3). However, the equations they proposed do not describe the conditions of this particular exchange, but represent entire market generalizations. Formally, this can be seen from the mathematical representations of these conditions. In case of Jevons, it is $\frac{dx}{dy} = \frac{x}{y}$, and in case of Walras it is $F_a(p_a) = F_b\left(\frac{1}{p_a}\right)\frac{1}{p_a}$, or in terms of x and y $F_a\left(\frac{y}{x}\right) = F_b\left(\frac{x}{y}\right)\frac{x}{y}$ (5.2) (F_a and F_b represent demand of goods A and B, x/y is price). No indices of participants (1, 2) are involved in these equations, in contrast to the equations of marginal utility, where these indices are explicitly present (for example see (4)).

If the general system of Equation (3) is written more rigorously, then both the participants (1, 2) of the exchange and the objects being exchanged (A, B) must be explicitly present in it as parameters:

$$\begin{cases} OB_{1,a,2,b}(x, y) = 0 \\ SU_{1,a,2,b}(x, y) = 0 \end{cases}$$

These parameters are explicitly represented in the marginal utility equations proposed by Walras and Jevons. However, another exchange condition presented by each of these authors does not contain the specified parameters 1 and 2. Thus, Jevons simply axiomatically introduces the formula of the "law of indifference", and Walras gives reasoning when some supply–demand curves are averaged over the entire market, and thus a common price for all is obtained. In both models, the price equation is independent on individual exchange. However, in reality, even in a large market, the prices of individual exchanges can vary and the correct model should reflect this fact. I am not suggesting here that the terms they proposed were incorrect. In fact, Jevons' condition was wrong, and Walras' condition was true. However, these were not the conditions of this particular exchange, but the market conditions averaged over parameters 1 and 2.

What can the first OB equation in system (3) be? LTV might come into play. According to LTV, when they engage in exchange, the parties compare the amount of socially necessary labor that is needed for the creation of the exchange objects. The condition of the exchange is the equal content of labor T in the objects of exchange. In other words, the exchange will occur if

$$T(x) = T(y), \text{ where x and y are the quantity of the exchange items O1 and O2.} \tag{6}$$

This equation offers an objective criterion for exchange and could be the first equation in system (3). However, the LTV is incomplete, that is, it is incapable of explaining every possible exchange uniformly, as any counterexample proves. Marx gave one such example in Das Kapital. He wrote: "Objects that in themselves are no commodities, such as conscience, honour, &c., are capable of being offered for sale by their holders, and of thus acquiring, through their price, the form of commodities" (Marx 1909). Here, Marx tried to escape a predicament—the content of labor is not found in the named objects of exchange, which means, according to his logic, that those objects cannot be exchanged. However, in reality, they do become objects of exchange, which forced Marx to seek explanations beyond the LTV. There are numerous examples of instances where no labor can be found in the objects of exchange, up to cases where money is paid for deliberate inaction, that is, the guaranteed absence of labor. Thus, LTV is not suitable for solving the exchange problem. To discover the condition that is necessary to compose a complete system of equations, I propose to regard exchange in more detail.

Consider the following proposition: both the exchange value and the use value of a desired object become available to the participants in exchange only when the objects of exchange are at the disposal of each participant. As long as an item does not belong to a person, they cannot access any of the value in that item. Within the framework of market relations, it is impossible to exchange or use an object that a person does not control. Marx wrote about it as follows: "In order to relate these [exchanged] things to one another as commodities, the guardians of commodities must relate to one another as persons whose will disposes of these things, so that each acquires the foreign commodity only with his will and the will of the other, both therefore only with their common will can appropriate someone else's goods, alienating their own". (translated by the author) (Marx 1867). Marx notes the need for an ability to dispose, an ability to fulfill the will of the commodity owner in relation to the commodity or, as I will discuss later, the necessity of "finding the commodity in the power" of the commodity owner. Here, I need to discuss the concept of power in more detail.

5. Power and Generalized Power

There are several approaches that look at the concept of power from different angles. Here, the situation with different views on the concept of power in sociology and political science is to some extent similar to the situation with different approaches to utility in economics, when different authors offer different definitions when they consider this phenomenon from various perspectives (Keller 2015). I will briefly recall now the different points of view on the concept of power.

Max Weber defined power as "the probability that one actor within a social relationship will be in a position to carry out his own will despite resistance, regardless of the basis on which this probability rests" (Weber 1957). The works of Harold D. Lasswell, Abraham Kaplan, Robert Dahl, Dorwin Cartwright, Steven Lukes, and Anthony Giddens presents a concept according to which "power arises in those social interactions where one of the subjects has the ability to influence the other, overcoming his resistance" (Ledyaev 2015). In another approach, followed by Talcott Parsons and Hannah Arendt, "power is viewed as a collective resource, as the ability to achieve some public good; the legitimate nature of power is emphasized, it's belonging not to individuals, but to groups of people or society as a whole" (Ledyaev 2015).

Each of these approaches attempts to explain the mechanisms for exercising power through either coercion or agreement. To the present ends, the mechanisms of power are less important than a description of power in terms that are applicable to exchange. The quote from Marx above indicates that the notions of will and disposal are likely to prove useful. It will be shown later that the concept of will plays an essential role in explaining exchange. Thus, for the purposes of this article, it would be reasonable to take Weber's definition as a basis, because it also relies on the concept of will. Now, an appropriate definition of power can be given. Nothing new has to be invented for this purpose. I need only highlight and slightly transform part of the quote by Weber: power is the ability to realize (exercise) the will (the ability to dispose) of the subject in relation to the object.

Power is often described in comparative terms. Phrases such as "they have a lot of power" or "this person has much more power than that person" can often be heard. Some researchers have argued about the measurability of power. Thus, in the works of Lasswell, Kaplan and Mills, the model of power is a zero-sum problem, that is, "there is a fixed 'quantity' of power in any relational system and hence any gain of power on the part of A must by definition occur by diminishing the power at the disposal of other units, B, C, D" (Parsons 1963). Thus, power turns out to be quantitatively measurable, and in fact the "law of conservation of power" is proclaimed. I adopt a similar quantitative approach, albeit without the conservation law (perhaps Parsons' consideration of this law is based on the kind of misunderstanding of the work of the aforementioned scientists, as shown by (Baldwin 1971)). Note that the word "probability" used by Weber in his definition of power is in agreement with the quantitative measurability of power. However, following Peter M. Blau, I used "ability" in the definition. The reason is that mathematical value of probability cannot exceed 1. However, in the case of power, the general measuring scale cannot be limited because one power can always be several times greater than another. As for the term "ability" in the definition of power, perhaps an example from physics would be appropriate, when energy is defined as the *ability* to do work. According to Bertrand Russell "the fundamental concept in social science is Power, in the same sense in which Energy is the fundamental concept in physics" (Russell 2004). Jonathan Hearn studied in detail the analogy between social power and physical energy and believed that the analogy is deep, ubiquitous, and sometimes more than an analogy (Hearn 2012).

It should be clarified that I am not mentioning economic theories of power here, since they do not offer the idea of measurability of power. For example, the evolutionary chain of theories of the firm (Alchian and Demsetz, Coase and Williamson, Hart and Moore) significantly address the issues of power relations, but power is not a measurable parameter.

I propose to return to the concept of transferring an object between exchange participants. Transferring is key for the parties to gain access to the benefits that they want.

How is the transfer actuated? First of all, as Marx rightly noted, "the will of [the parties] disposes... of things [objects of exchange]." In other words, the precondition for exchange is that the will of the participant can dispose of their object of exchange. How does the will of this subject relate to the object before and after the exchange? The nature of exchange items can vary. Material and informational objects (or more generally: tangible or intangible objects) can be exchanged, as can activity and inactivity. When it comes to the possibility of exercising the will in relation to an inanimate object, it is possible to speak of a right of ownership in relation to the object. However, in reality, items are sometimes exchanged that are not owned by the participants. For instance, a thief may well exchange a stolen object, even though the thief does not have ownership rights. The thief can dispose of the object without those rights because the object is in their power and they have the ability to exercise their will vis-a-vis the object, even without legal rights. The implication is that it is more accurate to speak not of ownership but of finding an object in power. In general, one can regard "ownership as the power to exercise control" (Grossman and Hart 1986). Grossman and Hart also refer in the same article to the Oliver Holmes' quote, which more fully expresses the idea: "the owner is allowed to exercise his natural powers over the subject-matter" (Grossman and Hart 1986). In the course of an exchange, objects must be swapped and a transfer must occur. In this way, the object passes from the power of one party to the control of another. Then, each participant loses the ability to dispose of their objects. However, they are able to dispose of, that is, to exercise their will in relation to the received objects.

The case is different when activity forms the object of exchange. Suppose that a worker transacts in labor at a construction site. In this case, every working day, for eight hours, the worker does not control their activities. Instead, a foreman does. By giving instructions to subordinates, the foreman exercises their will in relation to the subordinates. The foreman says what needs to be done; the worker obeys and performs the necessary work. Thus, within the framework of the contractual relationship that has arisen in the course of the exchange, the foreman exercises power over the worker. For eight hours, the worker is under the power of the foreman, who can dispose of his activity. In general, "After the exchange, power is in the hands of the capitalist, and its monetary equivalent in the pockets of the worker" (Palermo 2016).

In exchanges of both material objects and activities, transfer takes the form of a mutual transmission of the object of exchange to the power of the other party. To emphasize the unified nature of the events that transpire during the exchange, I use the term "generalized power," that is, the ability of the subject to exercise their will in relation to the object both in the case of material or informational objects and in the case of activities. Then, "transfer" in exchange is the mutual transfer of objects to the generalized power of the other party.

In general, no fundamental obstacles prevent the extension of the concept of power into the concept of generalized power. Generalized power includes both power over people and power over things or information. Generally speaking, the two cases differ only in the object to which the human will is applied. The ability to dispose of a material or informational object, power over such an object, means that a person can exercise their will in relation to an object and do what they want with it. The ability to control the activities of a person, power over a person, means that one can exercise one's will in relation to another, a subordinate, and give orders that the subordinate will obey. Walras wrote: "The object of bringing the human will to bear upon natural forces, that is to say, the object of relations between persons and things, is the subordination of the purpose of things to the purpose of persons. The object of exercising the human will on the will of others, in other words, the object of relations between persons and persons, is the mutual co-ordination of human destinies" (Walras 1954). Probably it would be logical to supplement this statement of Walras by saying that in the case of human relations, similar to the case of relations between persons and things, the object of exercising the human will is the subordination of the purpose of *one person* to the purpose of *another person*. In both cases, power is the ability to actuate will. In fact, possession (of an object) and dominion (over a person) merge naturally because both concern the application of the will of an individual to some object. Power is exercised in both cases, and it is directed at either objects that do not have their own will (material or informational objects) or to objects that do (people). This shows the natural essence of the term "generalized power," which combines different manifestations of power.

It follows that, at first, the object of exchange A is under the generalized power of the first participant in the exchange, H1. After negotiations with the second participant, H2, and the determination of the parameters of exchange between objects A and B, the two are transferred. At this moment, the generalized power of H1 over A disappears, as does the generalized power of H2 over B. There immediately arises a new generalized power of H1 over B and, accordingly, of H2 over A. Interestingly, power is not transferred in the same way as material objects—it does not pass physically from hand to hand. After all, the power of exchange participant H1 over object A, which exists before the exchange, is not exactly the same power as that of participant H2 over object A, which appears after the exchange. (It is important to note in parentheses that the behavior of generalized power in exchange is very similar to the behavior of utility, because the utility of the same object after the exchange is a different utility than it was before the exchange.) Nevertheless, there is a transfer of power. Initially, H1 had power over A. Now, H2 has power over A. It turns out that the true essence that is transferred at the moment of exchange is generalized power. Only after the transfer of generalized power can the participants in the exchange consume or exchange the received objects. Therefore, in the course of exchange, the transfer of power is primary vis-à-vis the transfer of use value and exchange value. The possibility of command or power must be transferred before the subject may enjoy the benefits that the object of exchange embodies. One of the founders of MUT Carl Menger wrote about the exchange, that command (power) of a certain amount of goods from one side is transferred to the other side and vice versa (Menger 2007).

It emerges that generalized power plays a key role in the second stage of exchange, the moment of transferring objects. Now, in order to reveal the role of power in establishing the proportion of exchange, I turn to the bargaining process. Let us model a standard negotiation. Suppose that two individuals, H1 and H2, engage in exchange. H1 offers goods A, and H2 offers goods B. The bargaining proceeds along the following lines:

1. H1 offers an exchange ratio of 2A for 7B ($2/7 \approx 0.28$);
2. H2 proposes 3A for 8B instead ($3/8 \approx 0.37$);
3. H1: 3A for 10B ($3/10 = 0.30$);
4. H2: 3A for 9B ($3/9 \approx 0.33$);
5. H1 accepts the offer.

The numbers in brackets indicate proportions (the number of A is divided by the number of B). In the course of bargaining, H1 is trying to lower the ratio and H2 is trying to increase it. In bargaining by the method of successive approximations, a certain final ratio is sought that will suit both parties. Different quantities of goods A and B are equated. These goods may not have anything in common. However, in the course of exchange, some commonality is found and compared quantitatively. So, what is measured or compared during the bargaining process? Is it labor, as Marx claimed? Or is it scarcity, as Walras wrote? As shown above, generalized power is mutually transferred during the exchange. The transfer of the object is the transfer of power over the object, which means that it is precisely generalized power that must be compared during the bargaining process. H1 and H2 compare what they transfer to each other and this is exactly and exclusively the generalized power. Moreover, generalized power must be compared *before* the exchange. *After* the exchange, other generalized powers will emerge on both sides.

Apparently, it is more important for an individual to measure the loss of what they had before the exchange than to evaluate their gains from it. Aristotle, in his analysis of exchange, wrote that "what belongs to us and what we give away always seems very precious to us" (Aristotle 1906). Kahneman and Tversky's well-known prospect theory later explained the relative importance of loss and gain in subjective assessments. The theory posits that "the disadvantages of a change loom larger than its advantages, inducing a bias that favors the status quo" (Kahneman 2011) (this phenomenon is called loss aversion). Therefore, assessing the loss of generalized power turns out to be the most important task of a participant in an exchange. It appears that the participants in the exchange must mutually evaluate how much generalized power each will lose before they can reach an agreement.

In view of the foregoing, I believe that while bargaining, participants compare the generalized power that they would lose as a result of a given exchange. As noted earlier, I proceed from the assumption that power is measurable, that is, that the generalized power B of the exchange participant H over the object of exchange O can be represented by a positive number

$$B = B\ (H, O), \text{ where } B >= 0.$$

Later, it will be seen that there is a direct way to measure and quantify generalized power. Therefore, this assumption is not just an analytical prop but also a mechanism that exists in actuality. If the bargaining process set out above is represented through the function B, the following sequence of estimates emerges:

1. B (H1, 2A) <= B (H2, 7B)—an estimate made by H1;
2. B (H1, 3A) >= B (H2, 8B)—an estimate made by H2;
3. B (H1, 3A) <= B (H2, 10B)—an estimate made by H1;
4. B (H1, 3A) >= B (H2, 9B)—an estimate made by H2;
5. B (H1, 3A) <= B (H2, 9B)—agreement H1.

Here, each estimate reflects the interests of the participants in the exchange in receiving more than what they give. Successive comparisons lead to two inequalities,

$$B\ (H1, 3A) >= B\ (H2, 9B)$$
$$B\ (H1, 3A) <= B\ (H2, 9B),$$

whence it follows that

$$B\ (H1, 3A) = B\ (H2, 9B)\text{—exchange condition.}$$

Thus, the exchange occurs only when the parties assess the generalized powers that they have in relation to the objects of exchange as being equal. Then, in the general case, the exchange condition is B1 (x) = B2 (y) where Bi(x) = B (Hi, x).

6. A Power Theory of Exchange

I have arrived at the power theory of exchange. The quantity of generalized power is the measurable basis of exchange. Before continuing, I will mention the results obtained by scholars in this direction. It should be noted that many sociologists have already highlighted the fundamental role of power in exchange. For the most part, these scientists considered not market exchange but social exchange, of which market exchange turns out to be a special case. In this approach, the concept of exchange extends beyond our framework into the more general problem of exchanges of values in society. These theories examine "the exchange of various types of activity as the fundamental basis of social relations on which various structural formations are based" (Kuznetsov 2012). The integration of power into the theory of social exchange is presented in the works of Peter Blau, George Homans, and Robert Emerson. Peter Blau wrote that "power refers to all kinds of influence between persons or groups, including those exercised in exchange transactions, where one induces others to accede to his wishes by rewarding them for doing so" (Blau 1964).

Some researchers have noticed the role of power in establishing the proportion of exchange, including in economic contexts. Thus, Emerson, summarizing the findings of several researchers, wrote: "Within economics proper, much discussion of indeterminacy in the x/y ratio concludes that it is a problem of power" (Emerson 1976). Furthermore, in analyzing the influence of power on the ratio of economic exchange, he concluded that the public power available to one of the parties to an exchange often skews the ratio in their favor. Emerson wrote about the emergence of an "unbalanced ratio" of exchange under the influence of power. He meant that if one side, party A, wield social power over another, party B, then the exchange ratio is likely to favor the first. However, this supposedly unbalanced ratio of exchange is premised on a misunderstanding of the role of power. Market exchange is always balanced in a sense that the exchange point (x, y) is a zero-sum point where an improvement in the conditions of one party must come at the detriment of another. The imbalance discovered by Emerson and others, which is caused by additional load, falls on the balance of exchange from party A's side. It is the power that A holds. Therefore, A can surrender less of the product, relative to a situation in which their power is absent. Thus, Emerson adds support to the proposition that it is power that is compared during the exchange. The weight of party A's power tips the ratio in their favor without disturbing the balance of exchange.

I mentioned that various researchers have distinguished between manifestations of power, such as coercion and agreement. As far as generalized power and exchange are concerned, power often manifests in agreements. However, if the terms of the exchange are violated or left unfulfilled, methods of social coercion and punishment can be applied. Thus, the exercise of power in exchange includes both contractual and coercive components.

Returning to the original exchange problem given by the system of Equation (3), the power exchange theory provides the objective equilibrium equation OB for the general system.

$$\mathrm{OB}(x, y) = B_1(x) - B_2(y) = 0 \tag{7}$$

From this, a system of exchange equations can be obtained.

$$\begin{cases} B_1(x) - B_2(y) = 0 \\ \varphi_1(a - x)\psi_2(b - y) - \varphi_2(x)\psi_1(y) = 0 \end{cases} \tag{8}$$

In fact, the first equation permits the determination of the objective proportion of exchange (price). The second equation compares this proportion (price) with the subjective scale of marginal utility and allows the absolute values of the variables x and y to be calculated. Earlier in the paper, I mentioned Walras and Jevons' exchange theories, in which additional conditions were employed to obtain a solution. Now, it can be said that these selfsame conditions are given by the objective equilibrium Equation (7). Recall how Edgeworth, who criticized Jevons and Walras, pointed out that the exchange problem described by the corresponding equations is solved under perfect competition, that is, when the number of agents in the market tends to infinity (Edgeworth 1881). According to the power theory of exchange, in the case of a large market, Equation (7) for each individual exchange is subject to much greater social influences due to competition. This influence reduces the differences between the various possible Equation (7) for the same type of object, reduces the existing price dispersion. However, even in a large market, a variety of prices is always possible. The price may depend on the individuals participating in the exchange, on their social status and connections, and on many other circumstances, the assessment of which is made when comparing the generalized power during the exchange. How do the OB equations for individual exchanges relate to the averaged Walrasian price equations?

If there are N exchanges on the market, then for each one we have the equation: $B_{1i}(x_i) = B_{2i}(y_i)$, where $0 \le i < N$. To go to the price view, let us perform the transformations:
$\left(\frac{B_{1i}(x_i)}{x_i}\right)x_i = \left(\frac{B_{2i}(y_i)}{y_i}\right)y_i$ or $x_i = \left(\frac{B_{2i}(y_i)x_i}{B_{1i}(x_i)y_i}\right)y_i$. Let us introduce the following notation for the coefficient at y: $x_i = p_{21i}(x_i, y_i)y_i$. If to sum up these exchange conditions for the entire market, we obtain: $\sum_{0 \le i < N} x_i = \sum_{0 \le i < N} p_{21i}(x_i, y_i)y_i$. In this case, the supply of

product A on the market will be $O_a = \sum_{0 \le i < N} x_i$ (in Walras's book, the supply is indicated by the letter O), and the supply of product B: $O_b = \sum_{0 \le i < N} y_i$. Hence:

$$O_a = \left(\frac{\sum_{0 \le i < N} p_{21i}(x_i, y_i) y_i}{\sum_{0 \le i < N} y_i} \right) O_b$$

Thus, for a global Walrasian price, we obtain:

$$p_b = \left(\frac{\sum_{0 \le i < N} p_{21i}(x_i, y_i) y_i}{\sum_{0 \le i < N} y_i} \right) = \frac{1}{p_a} \tag{9}$$

Note that Walras did not consider supply (O) but demand (D) as the primary factor (Walras 1954). Mathematically, this does not matter, since at the moment of exchange the values of O and D are equal. This is more similar to the question "which came first, the egg or the chicken". However, judging by the above reasoning for the justification of Equation (7), the supply looks as primary for determining the price, since what is given is measured.

This way, all of the different Equation (7) for individual exchanges can be aggregated into a single exchange ratio equation for all market participants (9). This ratio appears to be the very market price that Walras took for granted. Then, Walrasian "one price" gives rise to Jevons' law of indifference because if there is fixed price than "all portions must be exchanged at the same ratio" (Jevons 1924). Under the circumstances suggested by Jevons and Walras, Equation (7) provides the very conditions that they needed in order to obtain results.

Returning to exchange, its ratio may be influenced by various intrinsic properties of the object. The object of exchange can have many properties but not all are relevant to particular exchanges. I will call the relevant properties exchangeable. An object can be considered as a set of exchangeable properties because its other qualities play no role. Thus, within the framework of the exchange:

O = {M1, M2, M3... Mn}, where Mi are the exchangeable properties of the object O. (10)

It is important to note that function B = B (H, O) depends not only on the properties of the exchange object, but also on its owner's personality (H1, H2). The qualities of the exchange participant, both personal and public, play an important role in establishing the value of B. Therefore, the participant's personality affects the exchange ratio. Equation (7) does not establish the absolute value of the function B but only a ratio of quantities. However, there is an object of exchange that allows the absolute value of the function to be measured, and that object is money.

7. A Power Theory of Money

In this study, I define money as an object of exchange that only has one exchangeable property, quantity, which is a positive number. On the one hand, this definition implies that money has a certain exchange value because it is an object of exchange, that is, because people are ready to accept it in exchange for something else. On the other hand, money is defined as an abstract, imaginary object, a number. This approach resonates with John Maynard Keynes's view of the nature of money. In his book *Treatise On Money*, he stated that "money-of-account is the description or title" or "name or description in the [money] contract", so money acts as an abstract name for an accounting unit (Keynes 1914). Economic practice increasingly shows that money is a number. Indeed, most of the money in circulation in the world today comprises numbers stored in the memories of computers. Estimates suggest that the share of cash is 9–15% in some countries (Bruno et al. 2020). Even if the appearance of paper dollars is easy to distinguish from that of paper euros, dollars and euros are completely identical in their digital forms.

The invention of cryptocurrency has advanced the conceptualization of money as a number. When fiat currency is used, numbers are stored on special banking computers. In the case of cryptocurrency, the ledger is distributed among many computers across the globe. The numbers are not even stored securely on computers owned by the central bank of some country. However, cryptocurrency is a medium of exchange. In this way, it the same as any other currency (Ammous 2018).

That money is simply a number means that it can be used to measure generalized power. The condition of the exchange is that the magnitude of the generalized power of the two parties be equal. When object O is exchanged for money D, then the exchange condition is

$$B\ (H1,\ O) = B\ (H2,\ D). \tag{11}$$

Moreover, money has only one exchange property, the amount K.

$$D = \{K\} \text{ means } B\ (H1,\ O) = B\ (H2,\ \{K\}).$$

It was shown earlier that bargaining does not establish the absolute value of B but a ratio. As a result, absolute values can be set arbitrarily without loss of generality. According to the definition of money given above, there is a special object of exchange which is a number itself. It is this number, the amount of money, that serves naturally as a measure of the magnitude of generalized power. The assumption is that

$$B\ (H2,\ \{K\}) = K, \text{ and then}$$

$$B\ (H1,\ O) = K. \tag{12}$$

The implication is that the amount of money that is exchanged for object O measures the amount of generalized power that binds participant H1 to object O. I conclude that money measures the generalized power that a participant in an exchange has in relation to the object.

However, this proposition does not exhaust the role of money. In exchanging the object O for money D, participant H1 obtains the opportunity to use generalized power in the amount of K units in subsequent exchanges. Accordingly, money is not only measuring generalized power in the course of exchange, but it also attests (certifies, confirms, denotes, symbolizes, serves as an equivalent) the corresponding amount of generalized power in subsequent exchanges.

Thus, a power theory of money was built. The main purpose of money is the measurement and certification of generalized power. The relationship between money and power has already been the subject of scientific research before. The well-known American sociologist Talcott Parsons made a significant contribution to the field. In his article "On the concept of political power," Parsons demonstrates the parallel between money and power. He wrote: "I conceive power as such a generalized medium in a sense directly parallel in logical structure, though very different substantively, to money as the generalized medium of the economic process" (Parsons 1963). His approach underscores the analogy between power in the political system and money in the economic system.

If power is quantifiable and not a zero-sum game, then it can be created and erased. It was seen that this is exactly what happens when objects are transferred at the point of exchange. Generalized power over one object disappears, and generalized power over another object appears. There is no reason to suppose that the magnitude of the new power is equal to that of the previous one. Moreover, it is noticeable from the very type of the power function

$$B = B\ (H,\ O),$$

that the value of B depends on the exchange participant H in the same way in which it depends on the subject of exchange O. I noted that Equation (7) is objective. It may be thought that this statement contradicts the proposition that the function B depends on the personality of H, which can be understood as a subjective factor. However, that argument is false. The value of the function B shows the magnitude, figuratively speaking, of the "force of gravity" between the person H and the object O, which is measured objectively through bargaining. The value of the function B is set in a clash between the interests of different parties, a tug of war of sorts, where each tries to tear something away from the other. In other words, neither side is willing to allow the other to establish their desired value of B. The value of B depends on a person in the same way as, for example, height or weight. However, being measured objectively, it is objective.

Conversely, in the Jevons exchange Equation (4), the participants in the exchange set the values of the marginal utility functions exclusively. Moreover, the sides of Equation (4) equate not the absolute values of the marginal utility functions of the participants but their ratios. In fact, in Equation (4), both the left- and the right-hand side are the marginal exchange rates (or marginal rate of substitution) of the corresponding goods as measured by the internal coordinate systems of each participant. In other words, the values that are being equated are purely subjective. The left-hand side represents the marginal proportion in the "system of measuring the utility" for the first participant, $(\frac{\varphi_1(a-x)}{\psi_1(y)})$, and $(\frac{\varphi_2(x)}{\psi_2(b-y)})$ performs the same function for the second participant on the right-hand side.

If there is an exchange which is conditional on equality

$$B\ (H1, O1) = B\ (H2, O2),$$

then after the exchange, once O2 has passed to the power of H1 and O1 has passed to the power H2, it will generally be the case that

B (H1, O2) $\neq$ B (H2, O1). (This can be understood to mean that there are no conditions for the reverse exchange). Moreover, B (H1, O1) $\neq$ B (H1, O2) as well as B (H2, O2) $\neq$ B (H2, O1).

The actual values of the resulting generalized power on both sides can only be measured during the next exchange—it is unknown in the immediate aftermath of the transfer. Consumption cannot be the sole purpose of the exchange, and subsequent exchange for profit must also feature. It follows from previous reasoning that if a person H1 exchanges object O1 for O2 in order to make a profit, then their motivation is tied to the expectation that their generalized power will grow after the exchange.

$$B\ (H1, O1) < B\ (H1, O2).$$

This explanation also shows how profit is obtained in trading operations. The art of the merchant is to assess fluctuations in the magnitude of generalized power correctly.

One interesting similarity between utility and power in exchange should be noted here. It was mentioned above that both utility and power are similar in that their values before and after the exchange do not coincide. Now I will note another similarity. As one can see, the expectation of an increase in generalized power after the exchange motivates the parties. But the expectation of an increase in utility after the exchange also motivates the parties. Consequently, the motivation to exchange contains two parts: an increase in power (an objective component) and an increase in utility (a subjective component).

It is worth dwelling briefly on the issue of trading profit. If a merchant buys A for money D1 and then sells the same A for money D2, then "profit" means that D2 > D1. Suppose that objective condition of exchange OB is represented by a function F, which depends only on the object of exchange O: F = F(O). In this case, for trade operations of the merchant will be: F(A) = F(D1)—this is the condition of the first exchange and F(A) = F(D2) is for the second exchange. From this follows: F(D1) = F(D2), what is impossible (D2 > D1). It looks as if the objective condition of exchange OB depends only on the object of exchange, then trade profit is impossible. However, in reality, trading profits exist. This means that such functions, dependent only on O but independent on H, cannot be used to model exchange. For example, such functions measure labor in LTV and scarcity in Walras theory.

8. Money Creation

Power can be transferred and created. This is true of all types of power, including symbolic power in the form of money. Money is both created and transferred. The creation of money by public authorities, which in everyday life is often called "printing money", means that the current authorities, by their own will, create the symbols of generalized power—money. From the point of view of the Power Theory, this process differs little from other activities of the authorities to create other power documents—orders, decrees, etc. Just as in the political sphere, the creation of power documents means the corresponding powers for officials, so the creation of economic power documents (money) means the emergence of power in the economic sphere. The topic of money creation by authorities is an important issue in Modern Monetary Theory (MMT), which argues that since authorities are able to arbitrarily create money, a country that issues its own currency can never run out of money and will never become insolvent against its own currency (Mitchell et al. 2019). As you can see from the above reasoning, this logic of MMT finds its explanation within the Power Theory of Money: as long as the authorities run the country (have real power), objectively nothing prevents them from "printing money". However, it should be noted that literal adherence to such a recipe may not produce positive results. For example, during the economic crisis generated by the COVID-19 pandemic the growth of the money supply has been passed on to the financial markets and the price of assets such as Bitcoin or gold, instead of being evenly distributed in the economy (Echarte Fernández et al. 2021).

Direct creation of money by the authorities is not the only way for new money to emerge. Scholars have long noticed that the crediting activity of banks consists not only in lending available money, but also in creating new money. Previously, it was believed that the mechanism for creating money by banks was to issue the funds available from one client to other clients. Thus, the reuse of money formally increases the money supply available to clients. The state requirement to reserve part of the funds was considered a limitation of this process, that is, having the money of one client, the bank could give a loan to another only minus the fractional-reserve set by the state (de Soto 2009). This "money multiplier" theory is criticized today (Carpenter and Demiralp 2012), since in the actual operation of banks, the initial prerequisite for issuing a loan is not the availability of funds, but the existing demand for loans (McLeay et al. 2014). This means that banks' ability to create money is not limited by government regulations, but by the bank's willingness to take the risk. After creating new money in its accounts, a bank may need to make settlements with other banks or with the state, and then it will need money in the accounts of the central bank, that is, it will need to apply for a loan either to the central bank or to receive an interbank loan. That is, unlike the state, banks face restrictions when creating new money. From the point of view of Power Theory, banks also turn out to be centers for the creation of economic power in the form of money.

In general, one can say that the state turns out to be a source of not only political, but also economic power in monetary form, and the state can either create this power directly or allow the creation and subsequent distribution of this power to private banks.

In conclusion, it should be said about the existing results in this direction. Parsons drew similar conclusions about the parallel between power creation and money creation, and demonstrated analogies between the emergence of new power and the creation of new money (Parsons 1963).

9. Results

This Concludes the Summary of the Main Elements of the Power Theory of Exchange and Money.

The main results of this article are:

- The formal exchange model is a problem with two unknowns. To solve this problem, two independent equations of an objective and subjective nature are required. As far as the author knows, this approach is new.

- For a correct description of the exchange, both equations must depend on the participants in the exchange. In the classical approach, only one equation depends on the exchanging parties, and the second has a global average character.
- The concept of "generalized power" has been introduced, which makes it possible to understand the participation of power in the exchange process.
- A new power exchange theory is proposed, which explains the objective equation of exchange by comparing the magnitude of the generalized power of the exchange participant in relation to the object.
- A new power theory of money is proposed, which explains the essence of money by measuring the magnitude of generalized power in the course of exchange and certifying this power in subsequent exchanges.

10. Conclusions

This article proposed a formulation of the exchange problem in the form of a system of two equations with two unknowns. One of the equations represents objective conditions of exchange, and the other equation represents subjective conditions of exchange. This approach resolves the long-standing dispute between two approaches to the exchange model, MUT and LTV. These theories are viewed as competing, but it transpires that they represent different and complementary conditions of exchange: MUT represents subjective circumstances, while the LTV represents objective ones. It may appear that combining the two approaches would solve the exchange problem, but as noted in paper the LTV is incomplete and it is refuted by simple counterexamples. Therefore, to establish the objective conditions of exchange, I proposed another idea whereby the objective basis of exchange is the comparison of generalized power. This idea gives rise to a power theory of exchange that is complete and that applies to any exchange. In addition to explaining the nature of exchange, the power theory captures the essence of money. Money turns out to be a measure and a certificate of generalized power in exchange.

The limitations of this study should be noted. The proposed model describes economic exchange, but, for example, social exchange is arranged differently. Cases outside the scope of the proposed model should be considered separately.

As noted, some thoughts set out in this article are found in economic and sociological research in scattered and partial form. However, it is only when they are collated into a power theory of exchange that these thoughts coalesce into a single logical fabric. Moreover, the connection and interdependence between economic, sociological and political theories becomes clear.

The power theory of exchange and money opens up broad prospects for further research. Here, are some examples of directions for future research on this topic. Many sociologists point to the key role of power relations in the emergence of political structures in society. Based on the power theory, one can try to find a general approach to the emergence of both political and economic structures. Further, if to carefully consider the possibilities of transforming real power into the symbolic form of money and vice versa, one can study the political significance of some economic phenomena, such as profit. Understanding money as a symbolic form of power allows also to take a fresh look at the theory of the firm.

The further development of the power exchange theory will enable a deeper examination of both economic and socio-political phenomena.

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Financial Inclusion Indicators Affect Profitability of Jordanian Commercial Banks: Panel Data Analysis

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Abstract: Previous literature supports the view that the financial inclusion leads to economic growth and helps alleviate poverty; however, it is still unclear whether financial inclusion increases bank profitability. The study assumes that financial inclusion is significant in enhancing the economy and minimizing loan accounts, and along with this assumption, the deposit size decreases the Jordanian banks' profitability despite the fact that the financial services and access to them have no significant influence upon such profitability. The major profitability drivers examined in this study comprised financial inclusion and financial leverage. In this study, 13 Jordanian banks' data from 2009 to 2019 were examined to determine the above issue. The study applied fixed effects on a panel data regression model. The findings indicated that the number of loan accounts and size of deposits negatively and significantly impacted the profitability of the commercial banks in Jordan. However, the number of branches and ATMs had no significant effect on the bank's profitability. In sum, both leverage and bank size were the top two determinants of commercial banks' profitability in Jordan. Based on the findings, Jordanian policymakers can shift their focus to offering affordable financial services that support SMEs' loans and start-ups.

Keywords: financial inclusion; commercial banks; financial services; profitability; financial leverage; Jordan

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1. Introduction

Since the financial inclusion concept was introduced in 2005, it has received significant attention from researchers and policymakers (Kumar et al. 2021). Financial inclusion is defined as the availability and equality of opportunities to access financial services. It refers to a process by which individuals and businesses can access appropriate, affordable, and timely financial products and services (Chen et al. 2018). It is evident that financial inclusion plays an important role in economic development and the stability of the financial system (Ikram and Lohdi 2015; Ahamed and Mallick 2019).

More importantly, the emergence of smartphones and the Internet has led to increased financial inclusion and increased opportunities for accessing digital financial services (Arun and Kamath 2015; Kanobe et al. 2017). According to 2017 Gallup World Poll data, 93% of adults in high-income economies have their own mobile phones, compared with 79% in developing economies (Gallup 2018). According to the database of Global Findex, advances in digital technology are key to achieving the World Bank goal of Universal Financial Access by 2020 (World Bank 2017).

Financial inclusion is on the rise globally. The 2017 Global Findex database shows that 1.2 billion adults have obtained an account since 2011, including 515 million since 2014. Between 2014 and 2017, the share of adults who have an account with a financial institution or through a mobile money service rose globally from 62 percent to 69 percent. In developing economies, the share rose from 54 percent to 63 percent (World Bank 2017).

In the Jordanian context, the percentage of adults owing accounts in financial institutions showed an increase from 2014 to 2017 (25–42%). This trend was also noted in the percentage of adults owning a debit/credit card in the same period (19–31%) (World Bank 2017). In addition, the Central Bank of Jordan (CBJ) has encouraged financial institutions to strengthen financial inclusion in Jordan by issuing guidance in the form of bank instructions and rules, which are also applied to other financial service providers in Jordan.

Financial inclusion is increasingly important as a measure used by policymakers, in the majority of countries, to improve economic growth and sustainability development (Sharma 2016; Shihadeh et al. 2018; Oz-Yalaman 2019; Ozili 2020; Al-Own and Bani-Khalid 2021). Financial inclusion is a top priority for policymakers for a variety of reasons, the first being that it is a key tool for achieving the United Nations' Sustainable Development Goals (SDGs) (Sahay et al. 2015; Demirgüç-Kunt and Singer 2017). The second reason is the role of financial inclusion in enhancing social inclusion levels in many countries (Bold et al. 2012), and third, it assists policymakers and government to alleviate poverty levels (Chibba 2009; Neaime and Gaysset 2018). It also provides extra socioeconomic benefits and improves the efficiency and accessibility of financial products/services while assuring security and reasonable costs (Ikram and Lohdi 2015; Andrianaivo and Kpodar 2011; Sarma and Pais 2011; Cull et al. 2012).

Viewed from a macro-level perspective, financial inclusion is capable of attracting more participants from various economic segments to the formal financial system (Neaime and Gaysset 2018). While financially excluded people are largely reliant on cash transactions that are independent of the Central Bank's monetary policy, financial inclusion is essential in bringing them into the mainstream of the formal financial system and, as a result, improving the effectiveness of the monetary policy transmission mechanism. The majority of international institutions and organizations, including the International Monetary Fund (IMF), the World Bank, and the Group of 20 (G20), have lately created adoption efforts to emphasize the importance of financial inclusion to economic development and sustainability. Several non-governmental organizations such as the Bill & Melinda Gates Foundation, the Consultative Group to Assist the Poor (CGAP), and the Alliance for Financial Inclusion (AFI), have also taken initiatives to promote and improve access to quality financial services. This is exemplified by Bill Gates' statement, in which he predicted that by 2030, 2 billion people who did not previously have a bank account will be using banks to store money and their phones to make payments, and mobile money providers will provide a variety of services ranging from interest-bearing savings accounts to credit and insurance.

Empirical researches along this line evidenced that the increase in financial inclusion on a global scale could increase household income through enhanced welfare, reduced poverty, initiating and expanding business and risk management, which will eventually lead to expansive opportunities for the banking sector (Bruhn and Love 2014; Kim 2016; Zachosova et al. 2018; Zhang and Posso 2019). The increase in the number of individuals who are financially included in the formal financial system is predicted to benefit the bank as this would increase the demand for financial services offered by the bank. According to Boot and Schmeits (2000), financial inclusion assists in obtaining higher diversification in banks and lowering risks.

Furthermore, policies promoting financial inclusion often promote the adoption of cashless money transfer technology and encourage clients to use formal financial services to accelerate economic and financial development. In the long-term, with an increasing number of people and businesses obtaining access to and demanding financial products and services, and participating in the formal banking system, the shadow economy size can be minimized. The shadow economy's existence considerably influences financial inclusion and in turn, the growth of the economy (Hajilee et al. 2017).

Banks' strategies place a greater emphasis on resource investment to improve services or the introduction of new services to meet the needs of customers and achieve higher returns for optimal performance. Opening new bank branches, installing more ATMs, or implementing new e-facilities are examples of strategies that can have a major impact on profit, especially if the costs are unrelated to sales revenues (Shihadeh et al. 2018).

When talking about the problem of financial isolation, it is necessary to distinguish between two seemingly similar words: access and use. "Access" mainly refers to the provision of financial services, while "use" is determined by demand as well as supply (World Bank 2014). It is also critical to recognize the phenomenon of financial isolation, such as gradual withdrawal (isolation) from the financial services market. As the offer does not meet the needs of the client, people with low income, financial problems, or potential users of financial resources may come to him, but they will not want to use it. This is due to a lack of need or for cultural or religious reasons. The second type of exclusion, forced exclusion, is caused by the same factors mentioned above: a lack of income, discrimination against certain groups, a lack of branches because they are not commercially viable for financial institutions, high prices, or inappropriate products (Achugamonu et al. 2020; Kata and Walenia 2015; MetLife Foundation & Microfinance Centre 2014). Mylonidis et al. (2019) conclude that social participation has economically significant effects on financial exclusion. The results show that individuals who engage in pro-social religious behavior, as measured by charitable giving, are less likely to be financially excluded.

The objective of this paper is to examine the impact of financial inclusion on banks' profitability: Does more financial inclusion lead to better financial results? The answer to this question represents the major continuation of this paper, the analysis shows that the impact of financial inclusion on banks' profitability depends on the type of financial inclusion. The number of branches and ATMs had no significant effect on the bank's profitability, while the number of loan accounts and size of deposits have a negative impact on the profitability of the banks. In addition, to the best of our knowledge, little attention has been given in the literature to the response of banks' profitability to changes in financial inclusion in Jordan. To this end, the current study included indicators of financial inclusion in the analysis to examine the sensitivity of the profitability of 13 Jordanian commercial banks to these indicators during the period 2009–2019 in the panel data framework.

In the present work, financial inclusion is measured by several indicators and they are: availability of financial service, access to financial service, use of financial service, and financial inclusion index.

2. Literature Review

According to most empirical studies, financial inclusion leads to increased economic growth and a more stable banking system (Sharma 2016; Ahmed and Salleh 2016). The impact of financial development and financial innovations on the economy and financial system has been the subject of theoretical and empirical research in recent decades (Gebrehiwot and Makina 2015).

On the other hand, financial inclusion may pose a danger to financial system stability, with high potential risks linked to increased borrowing by low-income individuals (Van et al. 2021a) and therefore, financial inclusion outcomes on the financial system have to be examined, particularly as policymakers have begun viewing it as a priority around the globe (Ali et al. 2020; Sarma and Pais 2011). Added to this, related studies also indicated that efforts towards promoting financial inclusion have led to higher welfare, lower poverty level, and lower income inequality (Beck et al. 2005; Chibba 2009; Aduda and Kalunda 2012; Cull et al. 2012; Morgan and Pontines 2018; Kim 2016; Neaime and Gaysset 2018; Shihadeh et al. 2018). Similarly, empirical studies have shown that financial inclusion among small enterprises and lower socioeconomic groups—particularly those who find it difficult to expand their investments and conduct daily financial transactions utilizing the official financial system—is essential for their success. (Demirgüç-Kunt and Klapper 2012; Kim 2016; Iqbal and Sami 2017).

Although the topic has been of current interest among researchers and regulators, no universally accepted definition of the financial inclusion concept has been proposed as yet (Aduda and Kalunda 2012; Tita and Aziakpono 2017). The Center for Financial

Inclusion (CFA) described financial inclusion as a state within which everyone who uses it has access to a full variety of quality financial services, at reasonable prices, conveniently, and with respect and dignity. Other related studies (Ratnawati 2020a, 2020b; Ilahiyah et al. 2021; Na'im et al. 2021) described it as a process that ensures that marginalized groups, such as the weaker parts and low-income groups, have access to suitable financial products/services at reasonable costs in a fair and transparent manner through mainstream institutional actors.

Meanwhile, the World Bank referred to financial inclusivity as the access to invaluable and affordable financial products and services that satisfy the needs of the individual for insurance, credit, savings, payments, and other transactions (Demirgüç-Kunt and Singer 2017). Another definition of the financial inclusion concept came from Sarma and Pais (2011) and Sarma (2008) who described it as a process that ensures the ease of access, availability, and usage of the formal financial system for all members of an economy. Other relevant studies such as Allen et al. (2016) and Ozili (2018) defined it as the process where individuals, particularly poor ones, have access to basic financial products and services by using the formal financial system. Financial inclusion, according to Hannig and Jansen (2010) is the absence of price or non-price barriers in accessing or using financial services.

Some other authors in the literature described financial inclusion as the antithesis of financial exclusion, where the latter comprises the process of preventing specific social groups and individuals from having access to the formal financial system (Leyshon and Thrift 1995). Similarly, Carbó et al. (2005) defined financial exclusion as, broadly, the inability (however occasioned) of some societal groups to access the financial system. According to Conroy (2005), financial exclusion is a process that hinders poor and disadvantaged social groups from accessing formal financial systems in their own countries. Financial exclusion was described by Mohan (2006) as the situation that reflects the lack of access by specific societal segments to appropriate, fair, low-cost, and safe financial products and services from mainstream providers. Meanwhile, Cámara and Tuesta (2014) referred to the financial inclusion system as one that maximizes usage and access, while minimizing involuntary financial exclusion. Bhanot et al. (2012) explored the factors which are crucial in determining the extent of financial inclusion in geographically remote areas. The results showed that the level of financial inclusion in northeast India remains very low. Income, financial information from various channels and awareness of self-help groups (SHGs), and education are influential factors leading to inclusion. Nearness to post office banks increases the likelihood of inclusion. Factors such as area terrain and receipt of government benefit individually do not facilitate inclusion. However, recipients of government benefits in plain areas showed an increased level of inclusion.

In addition to the differences in the definitions of financial exclusion and inclusion in literature, studies have also pointed out differences among non-users or those that are involuntary excluded/unbanked. The first group comprises individuals and businesses that are unbankable by financial institutions owing to their lack of sufficient income or there being too high a lending risk. The second group may be discriminated based on social, religious, or ethnic reasons, while the third one may be because of the contractual and legal framework that limits financial institutions from extending towards specific groups, as in so doing, it may be too costly, or the financial services prices may be too high for such a group (World Bank 2008; Kim 2016).

Therefore, based on the above different groups, and definition of both financial exclusion and inclusion, this study considers financial inclusion as the situation where individuals/firms have easy access to useful, affordable, and suitable financial products and services to satisfy their transactions, demands, savings, credit, insurance, and financial services types at an equitable price and in a sustainable manner.

More importantly, financial inclusion is becoming a popular paradigm in the development of finance, owing to its key role in easing access to formal financial services through the provision of bank accounts, credits, and saving through financial institutions (Mohan 2006; Cull et al. 2012; Zins and Weill 2016; Iqbal and Sami 2017). In contrast, financial exclusion outcomes can be detrimental and can lead to lower investment because of limiting access to credit or enabling the use of informal financing resources at significant rates of interest (Sarma and Pais 2011; Kim 2016).

Empirical findings in this line of study followed various themes in financial inclusion, indicating its potential to enhance the growth of the economy and the stabilization of the financial system. More specifically, empirical studies revealed and evidenced the key role that financial inclusion plays in economic growth and financial stability in several nations (Kim et al. 2018; Neaime and Gaysset 2018). Furthermore, despite the fact that some of them conducted an investigation into the relationship between financial inclusion and the profitability of banks, and these include Shihadeh and Liu (2019) and Ikram and Lohdi (2015), the findings concerning the effect of financial inclusion on the profitability of banks is still inconclusive.

Related studies include Kumar et al. (2021), who sampled 122 Japanese banks and obtained data from 2004 to 2018 to determine the impact of financial inclusion on the profitability of the banks. They found a positive relationship between the number of branches (proxy of financial inclusion) and the bank's profitability (ROA and ROE). Contrastingly, the authors found that financial inclusion in the form of the number of loan accounts and ATMs had no significant relationship to the profitability of the banks.

Moving on to other studies of the same caliber, Chen et al. (2018) and Shihadeh and Liu (2019) found a positive effect of financial inclusion on profitability, the former being measured by the number of branches. In Shihadeh and Liu (2019), with a study sample of 189 countries (national level) and 701 banks, the authors evidenced the positive impact of financial inclusion on the banks' activities, which in turn led to higher returns. They indicated that the number of branches had a positive relationship with ROA, ROE, and NI.

Moreover, Shihadeh et al. (2018) examined the effect of financial inclusion on gross income and ROA of 13 commercial Jordanian banks using data from 2009 to 2014. Six financial inclusion variables were employed, namely SMEs' deposits and credits, ATMs, ATM services, and new services and credit cards (predictors of the variable). Based on the obtained results, the profitability of the banks was affected in a positive direction by the number of ATMs, number of ATMs' services, and SMEs' credits, but it was not affected by credit cards and new services as well as SMEs' deposits.

The above finding was also similar to that reported by Ahamed and Mallick (2019), the focus of which is on the proliferation of bank branches, a decrease of banks' default risk and the non-performing loans, which ultimately enhances the revenues of the banks. Akhisar et al. (2015) investigated the effects of the bank's profitability performance of electronic-based banking services. The effects of ROA and ROE performance were analyzed as data, which are 23 developed and developing countries' electronic banking services through 2005 to 2013, by dynamic panel data methods. Results showed that bank profitability of developed and developing countries affected from the ratio of the number of branches to the number of ATMs is highly significant and electronic banking services insignificant.

Contrastingly, Jouini (2021) investigated the effects of financial inclusion on the performance of the banking sector, measured by the return on assets, for a set of 11 Arab countries over the 2013–2019 period in the dynamic panel data framework. In addition to financial inclusion indicators, they included bank-specific factors and macroeconomic variables into the analysis. The study revealed that the bank-specific factors are the most influential on banks' profitability, and to a lesser extent, the macroeconomic variables, regarding financial inclusion, the study did not find any evidence of significant effects of the distribution of ATMs and the number of bank branches on the return on assets.

In other studies, a positive relationship was found between banks' revenues and the number of bank branches (Bernini and Brighi 2018), and between branch expansion and bank efficiency for the years spanning from 1999 to 2009 (Harimaya and Kondo 2012). In the latter, a sufficient level of branch expansion should be conducted to experience a positive impact on profit and cost reduction. The empirical findings of Ikram and Lohdi (2015), in their examination of the effect of financial inclusion on Pakistani banks' profitability, indicated that financial inclusion variables (financial services' use, access to financial services, and cost of financial services) had no significant relationship with the generation of the banks' revenues.

Shihadeh (2020) used a sample of 271 banks in MENAP countries to examine the influence of financial inclusion on bank risk and bank performance, and based on the data analysis, financial inclusion had a negative relationship with banks' risks but a positive relationship with bank performance. In the Asian countries, Van et al. (2021b) documented that a higher financial inclusion level had a positive effect on the stability of the bank sector as well as higher banks' revenues. At the same time, it had a negative effect on the banks' costs, but a positive effect on market share.

As evident from the above-reviewed studies, empirical studies in the literature that were dedicated to examining the effects of financial inclusion on bank profitability depended largely on accounting-based measures (ROA and ROE). In the present paper, the market-based measure (Tobin's Q) is adopted as the banks' profitability proxy—it is a measure that is obtained by the total market value over total assets. It is an effective profitability measure as it is capable of capturing future growth opportunities and long-term financial performance as predicted by the stock market (Aivazian et al. 2005; Alyousef et al. 2019).

The study findings can be leveraged by the governments and regulators, particularly when it comes to the effect of financial inclusion on the performance of banks, and an insight into the financial inclusion strategies' outcomes. The study investigates the relationship between profitability measures and financial inclusion indicators in the Jordanian banking sector based on the literature reviewed and the gap in the empirical studies concerning the topic.

Furthermore, studies indicated that bank leverage and bank size can be used to predict its profitability; for instance, Ramadan et al. (2011) revealed that one of the primary determinants of a bank's profitability is its lending activities. Bank size has also been found to control economies of scale and, as such, it is one of the determinants of a bank's profitability. However, empirical results indicated that the relationship between size and profitability has yet to be confirmed, with findings being inconclusive. Some studies such as Ramadan et al. (2011) and Almumani (2013) revealed no significant bank size-profitability relationship, whereas others such as Almazaril (2014) found a negative relationship between the two. Some others found a positive relationship between bank size and bank profitability (Khrawish and Al-Sa'di 2011), and thus, these variables (financial leverage and size) were considered as control variables in the present study to be analyzed through regression.

3. Methodology

This study primarily aims to examine the effect of financial inclusion on the performance of commercial banks listed on the Amman Stock Exchange (ASE) in Jordan. Under this section, the methodology adopted in analyzing statistical relationships between the variables is presented, beginning with the definition of the study population and sample, the study variables, and the measurement methods. The section also covers the analysis methods and data collection sources.

3.1. Materials

To begin with, the study population comprises the entire banks listed on the ASE, while the sample of the study consists of commercial banks from the same list. Table 1 tabulates the sample selection procedure for the period 2009–2019, excluding all foreign and Islamic banks due to their distinct regulations that differ from the general commercial local banks.

The required data was gathered from secondary sources in the form of annual reports of banks, available on the Amman Stock Exchange website (https://www.ase.com.jo/ar), accessed on 10 December 2020, and the Securities Depository Center website (http://www.sdc.com.jo), accessed on 10 December 2020. The study focused on the years spanning from 2009 to 2019.

Table 1. Sample selection procedure.

Bank Population. All banks listed in (ASE)	24
Excluded: Foreign banks	7
Jordanian Islamic banks	3
Islamic foreign banks	1
Final sample (commercial)	13

With regards to the measurement of the variables, Tobin's Q (dependent variable) was measured as the total market value over total assets—this measure is deemed to be a more optimum profitability measure as it is capable of capturing future growth opportunities and long-term financial performance as predicted by the stock market (Aivazian et al. 2005; Alyousef et al. 2019), and as such, the paper adopts a market-based measure (Tobin's Q) to represent a bank's profitability.

Moving on to financial inclusion, several dimensions of the concept have been provided by researchers and institutions, which are as follows:

First, Availability of Financial Services (AFS): It is important for the comprehensive financial system services to have ready availability, and this may be reflected through the number of bank outlets and/or the number of ATMs, or the number of employees per customer in the bank, or the number of bank branches, for availability measurement.

Second, Access to Financial Services (SFS): this procedure ensures access to financial services and the provision of timely and sufficient credit when required by the marginalized groups such as the poorer sections and low-income sections, at a cost that is affordable for them (Dienillah et al. 2018).

Third, Use of Financial Services (UFS): in this dimension, the impetus is driven by the underbanked or marginally-banked concept as mentioned by Kempson et al. (2004), where in some nations with a higher level of banking, several people do not make use of the services offered although they have a bank account. Two primary services of the banking system, namely credit and deposit were used in the paper for the measurement of this variable.

3.2. Econometric Model

The simplest way to estimate and measure regression in an attribute is with aggregate regression, which involves estimating a single equation over all the data jointly (Brooks 2008):

$$y_{\mathrm{it}} = \alpha + \beta x_{\mathrm{it}} + u_{\mathrm{it}} \tag{1}$$

where y represents the dependent variable, i unit, t time, x the independent variables, and u represents the random error term.

For financial research, there are two main models that can be applied. The fixed effects model and the random effects model (Verbeek 2012):

$$y_{\mathrm{it}} = \alpha + \beta x_{\mathrm{it}} + u_i + V_{\mathrm{it}} \tag{2}$$

In general, the random effects model is more efficient than the fixed effects model because it measures fewer parameters.

The study tests the financial inclusion effect on the financial performance of commercial banks in Jordan by applying the multiple linear regression model, which is as follows:

$$TQ_t = \alpha_0 + \beta_1 AFS_{\mathrm{it}} + \beta_2 SFS_{\mathrm{it}} + \beta_3 UFS_{\mathrm{it}} + \beta_4 II_{\mathrm{it}} + \beta_5 L_{\mathrm{it}} + \beta_6 S_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{3}$$

In the above equation, TQ_t denotes Tobin's Q, AFS_{it} denotes availability of financial services, SFS_{it} denotes access to financial services, UFS_{it} denotes the use of financial services, II_{it} denotes inclusion index, L_{it} denotes financial leverage and is used as control, and S_{it} denotes the size of the commercial bank in Jordan and is used as a control variable. Finally, ε_{it} represents error terms.

The panel time analysis data is employed, including the characteristics of cross-sectional data as well as time series data in an approach that is characterized by the consideration of the effect of individual and time factors during the estimation of regression equations. The study used two statistical analyses and they are—descriptive statistics (means, standard deviations, minimum and maximum) and regression diagnostics (Hausmann test, multicollinearity test).

4. Empirical Results

This study is focused on investigating the effect of financial inclusion on the performance of Jordanian commercial banks for the years 2009 to 2019, using a panel data model. Prior to the regression analysis, a stationarity test was carried out for the independent variables of the model. In addition, the stability of the study variables data was tested using the Augmented Dickey–Fuller test (Dickey and Fuller 1979) and Phillips–Perron test (Phillips and Perron 1988)—these were also used to determine the time series data stability for the period of study, as unstable data could lead to inaccurate results of the regression.

The descriptive analysis results of the study variables are tabulated in Table 2. The analysis covers the mean, median, standard deviation, and maximum and minimum values for every study variable.

Table 2. Summary of statistics.

	Mean	Max	Min	Std. Dev.
TQ	1.088511	2.569251	0.251348	0.483238
AFS	129.942	346	19	90.76027
SFS	3145.659	9802	0	25.22979
UFS	0.09266	9.350473	0.00037	0.794728
II	4.140301	74.31163	9.93×10^{-6}	12.57232
L	0.85984	0.924952	0.78036	0.026403
S	9.32458	10.42043	8.477959	0.401994

One of the most common issues that statistical estimation of regression coefficients often faces is multicollinearity. This generally stems from the existence of a strong correlation between the study's independent variables (Gujarati 2014). The results of the Pearson correlations between the variables in the multivariate analysis are presented in Table 3, and from the table, the highest pair-wise correlation coefficient between variables is 0.774, which indicates no multicollinearity issue.

Table 3. Correlation Matrix.

	TQ	AFS	SFS	UFS	II	L	S
TQ	1						
AFS	0.1038	1					
SFS	−0.0047	0.0936	1				
UFS	−0.136	−0.0001	−0.017	1			
II	0.1827	−0.0972	−0.019	−0.0113	1		
L	−0.237	0.1488	−0.066	0.11136	−0.058	1	
S	−0.013	0.7745	0.0703	0.01348	−0.093	0.1252	1

The stability of the time series data of the variables, as mentioned, was tested by using both the Dickey–Fuller and Phillips–Perron tests. This test is important as unstable time series data could lead to inaccurate regression results. The two tests were thus conducted at the level and first difference of the study variables.

The entire variables were found to be unstable at the level and the nihilistic hypothesis providing the instability of the time series was accepted (Table 4). As such, the first difference was taken for the variables, after which a re-test was done (Dickey–Fuller and Phillips–Perron), by a moral value of lower than 5% for the tests. The study accepted the alternative hypothesis, stabilizing the study variables and indicating that the effect of temporary shocks fades in the long run, particularly since the Phillips–Perron test considers random errors, and this holds true for the Dickey–Fuller test.

Table 4. Unit root test results (ADF and PP).

		ADF	PP	Result
TQ	Level	12.8764	15.3727	Non-Stationary
	First difference	50.5403 ***	77.0847 ***	Stationary
AFS	Level	66.9278 ***	66.4362 ***	Non-Stationary
	First difference	63.7301 ***	79.1936 ***	Stationary
SFS	Level	32.7795	47.4273 **	Non-Stationary
	First difference	44.0050 **	143.177 ***	Stationary
UFS	Level	26.4161	55.9052***	Non-Stationary
	First difference	62.6269 ***	177.429 ***	Stationary
II	Level	18.5900	57.7385***	Non-Stationary
	First difference	33.0247 *	152.279 ***	Stationary
L	Level	12.0385	7.10706	Non-Stationary
	First difference	45.7422 **	87.8196 ***	Stationary
S	Level	11.4736	16.7457	Non-Stationary
	First difference	69.2081 ***	73.8610 ***	Stationary

Note: ***, **, * indicate statistically significant at 1%, 5%, and 10% level, respectively.

The p-values of the F-test at the significance level of 1% are presented in Table 5. This shows that the regression models had better data fit compared to models with no predictor variables and that a probability lower than 0.05 means that the null hypothesis is rejected, making the Fixed Effect Model more suitable for the analysis of the study model. The main study model investigates the impact of financial inclusions on commercial banks' performance in the context of Jordan and the results of the fixed effect model's regression analysis are tabulated in Table 5.

To begin with, the availability of financial services was found to have no significant impact on the profitability (with Tobin's Q as the proxy) of Jordanian commercial banks (coefficient of -0.000429, $p > 0.10$), Similarly, for the access to financial services, no significant impact was found on the commercial banks' profitability (with Tobin's Q as the proxy) (coefficient of 1.19×10^{-7}, $p > 0.10$). This result is aligned with that reported by Kumar et al. (2021).

Moving on to the use of financial services, based on the results, the use of financial services has a significant negative impact on Tobin's Q (coefficient = -0.074335, $p < 0.01$). This was the same for the index of financial inclusion, which was found to have a significant impact on the commercial banks' Tobin's Q but in the positive direction (coefficient = 0.000107, $p < 0.01$). This is aligned with the result revealed by Kumar et al. (2021), Shihadeh and Liu (2019), and Chen et al. (2018).

Table 5. Panel data fixed effect model regression results.

Variable	Coefficient	t-Statistic	Prob.
C	8.407168	4.394342 ***	0.0000
AFS	−0.000429	−0.35484	0.7233
SFS	1.19×10^{-7}	1.171422	0.2438
UFS	−0.074335	−2.75102 **	0.0069
II	0.000107	4.255236 ***	0.0000
L	3.497607	2.196482 *	0.0300
S	−1.102226	−3.88012 ***	0.0002
R-squared	0.785839		
F-statistic	24.25871	Durbin–Watson	1.676
Prob (F-statistic)	0.00000		
Hausman test			
Test summary	Chi-sq. statistic	Chi-Sq. d.f.	Prob.
Period random	20.703546	6	0.0021

Note: ***, **, * indicate statistically significant at 1%, 5%, and 10% level, respectively.

The size was found to have a negative and significant impact on the financial performance of commercial banks in Jordan, which is consistent with the results reported by prior studies (Tan and Floros 2012; Almazaril 2014).

5. Conclusions

It is evident from this study and the obtained results that financial inclusion has a significant role in banks. The findings indicated that the number of loan accounts and size of deposits negatively and significantly impacted the profitability of the commercial banks in Jordan. This result supports prior studies by Kumar et al. (2021), Shihadeh and Liu (2019), and Chen et al. (2018). However, the number of branches and ATMs had no significant effect on banks' profitability. In sum, both leverage and bank size were the top two determinants of commercial banks' profitability in Jordan. Based on the findings, Jordanian policymakers can shift their focus to offering affordable financial services that support SMEs' loans and start-ups.

Banks should also motivate households towards assets' diversification as opposed to just depending on cash and deposits. Banks, as well as other financial institutions, need to maintain their asset management fees to promote banking services' usage. Future studies can extend the examination by determining the effects of financial inclusion variables on bank risks. The policy implications of this study are that Jordanian commercial banks should increase their profitability and achieve the best results from financial inclusion. They must develop policies to promote financial inclusion. This implies that Jordanian commercial banks must be creative and innovative in their efforts to implement financial inclusion policies. Such policies should aim to increase the number of loans granted by providing affordable financial services to support SMEs' loans and start-ups.

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Cryptocurrencies and Tokens Lifetime Analysis from 2009 to 2021

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Abstract: The success of Bitcoin has spurred emergence of countless alternative coins with some of them shutting down only few weeks after their inception, thus disappearing with millions of dollars collected from enthusiast investors through initial coin offering (ICO) process. This has led investors from the general population to the institutional ones, to become skeptical in venturing in the cryptocurrency market, adding to its highly volatile characteristic. It is then of vital interest to investigate the life span of available coins and tokens, and to evaluate their level of survivability. This will make investors more knowledgeable and hence build their confidence in hazarding in the cryptocurrency market. Survival analysis approach is well suited to provide the needed information. In this study, we discuss the survival outcomes of coins and tokens from the first release of a cryptocurrency in 2009. Non-parametric methods of time-to-event analysis namely Aalen Additive Hazards Model (AAHM) trough counting and martingale processes, Cox Proportional Hazard Model (CPHM) are based on six covariates of interest. Proportional hazards assumption (PHA) is checked by assessing the Kaplan-Meier estimates of survival functions at the levels of each covariate. The results in different regression models display significant and non-significant covariates, relative risks and standard errors.Among the results, it was found that cryptocurrencies under standalone blockchain were at a relatively higher risk of collapsing. It was also found that the 2013–2017 cryptocurrencies release was at a high risk as compared to 2009–2013 release and that cryptocurrencies for which headquarters are known had the relatively better survival outcomes. This provides clear indicators to watch out for while selecting the coins or tokens in which to invest.

Keywords: cryptocurrency; blockchain; survival function; risk; weight; hazard ratio

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1. Introduction

Cryptocurrencies are digital currencies in which transactions are verified and records maintained by decentralized systems known as blockchains. Blockchains use cryptography or a third-free peer-to-peer electronic system, rather than a centralized trade in which transactions are made by the banks (Angela 2016). Transacting a cryptocurrency is mobile, non-taxable and does not require bank intermediary. Blundell-Wignall (2014) points that digital cash cannot have multiple copies. Hence, a cryptocurrency cannot be used more than once, unlike the bank services where multiple transfers are common.

Cryptocurrecies operate either as coins or tokens. Crypto-coins are native from their own blockchain whilst tokens are built on top of another existing blockchain (Wu et al. 2018). An important number of cryptocurrencies use Euthereum network as an alternative to standalone. Many other known networks include Waves, Stellar, Nem, Couterparty, Bitshares, Achain, Omni, Neo, Ardor, Qtum, Icon and Ubiq. The discretion in cryptocurrency transaction makes a more secure and reliable modern mode of payment as suggest manuscripts such as Blundell-Wignall (2014), Hendrickson et al. (2016) or Urquhart (2016).

The cryptocurrencies release started with the Bitcoin in 2009 Blundell-Wignall (2014). The other popular cryptocurrencies that followed include Litecoin (2011), Peercoin (2012), Ripple (2012), Alphacoin (2013–2014) and Aircoin (2014–2016). As for the year 2021, the new cryptocurrencies include Bogged Finance (2021) and Recharge Finance (2020). The total number of cryptocurrencies in 2021 exceeds 6000 in which around 2000 are inactive (or dead) (Best 2022). The high rate of death of cryptocurrencies has been a barrier of many investors. The risk of collapsing of a number of cryptocurrencies has persuaded some governments to ban such digital financial markets with argument that cryptocurrency trade could facilitate illegal transactions and disrupting the government activities (Hendrickson et al. 2016). However, El Salvador officially adopted Bitcoin as legal tender on 9 June 2021, making it the first country to do so (Thul 2021). In some other countries such as Panama, Brasil, Paraguay, Mexico and Argentina, the governments are hand in hand with the researchers on sustainability of Bitcoin for a future adoption (Thul 2021).

In 2020, the globe was under a relatively rising situation of the outbreak of COVID-19 and at the same time, the relatively high degree spillover of Bitcoin was observed (Xiao et al. 2021). The trade of cryptocurrencies was then globally affected (Youssef et al. 2021). Azimli (2020) suggests that COVID-19 pandemic impacts the financial market through the high level of economic policy uncertainty. The unknown future situation of COVID-19 leads to low cash flow expectations, resulting in possible stock market depreciation (Azimli 2020).

Several studies on cryptocurrencies emerged in many domains such as Mathematical Sciences, Financial Economics and Engineering. Mathematical and statistical modeling on cryptocurrency is found for example in (Gatabazi et al. 2019a, 2019b, 2019c, 2019d) and Chan et al. (2017). Mba and Wang (2019) used copula in describing cryptocurrencies in financial economics framework, a field in which many other manuscripts including Urquhart (2016) and Angela (2016) analyse cryptocurrencies. However, the scientific analysis on the lifetime of cryptocurrencies is not yet popular. To understand the event history analysis of cryptocurrencies and the associated factors may adopt another insight by which the researcher may predict accurately the future of these digital currencies.

The present study uses the time-to-event data analysis for estimating the life-time and the factors of death for cryptocurrencies during the study time ranging from 2009 to 2021.

In addition to the introductory section, the study is subdivided as follows: Section 2 presents the methodology of the study. Section 3 presents the main results and interpretation and Section 4 gives a conclusion.

2. Methodology

This part introduces the time-to-event analysis, discusses the time-to-event regression analysis and then presents the dataset of interest. Preliminary analysis will be displayed by the graphs and the useful statistical tests.

2.1. Concept of the Time-to-Event Data Analysis

The time-to-event analysis or survival analysis aims at making the inference of the time elapsed between the onset of observations until the occurrence of some event of interest. The related regression model expresses the dependence of time-to-event on predictor variables. Methods used in general statistical analysis, in particular in regression analysis, are not directly applicable to survival data due to censoring and truncation. Hosmer et al. (2008) describe three types of censoring: *right censoring* arising when an individual is not subject to the event until the end of study due to either loss to follow up, or the event has not occurred at the end of the study, or the event has occurred from another cause not related to the cause of interest. *Left censoring* arises when an individual experienced an event before the onset of the study. *Interval censoring* refers to when the event occurs within some interval in the study time, or the individual dropped out or observed the event at an unknown time before study termination for reasons unrelated to the study, or the individual was lost to follow-up in an interval between two specified time points. Two types of truncation described in Klein and Moeschberger (2003) are the *left truncation* and the *right truncation*. Left truncation occurs when subjects under a survival study have been at risk before the study time. Right truncation arises when interest is only on individuals who have experienced the event by a specified future time before study termination. In this study, interest will be only on right censoring.

In time-to-event analysis, a non-negative random variable representing the time-to-event is generally characterized by three fundamental functions: the probability density function (for continuous random variables) or probability mass function (for discrete random variables), the survival function and the hazard function as detailed in Hosmer et al. (2008). The hazard function is also known as risk function or intensity rate (Hosmer et al. 2008). Any of these three functions can be uniquely determined from at least one of the other two functions (Collet 2003; Hosmer et al. 2008).

2.2. Comparison of Two or More Groups of Survival Data

Two or more groups survival time may be compared by using the plots of the survival functions in one system of axes. Log-rank and Wilcoxon tests are popular tests for comparing survival functions (Collet 2003; Klein and Moeschberger 2003). The tests are based on the following hypotheses:

H0: *No difference in survival experiences of the individuals in the groups,*

H1: *There is difference in survival experiences of the individuals in the groups.*

In several studies, statistical significance is based on comparing p-values to a specified level of significance, α Generally $\alpha = 0.05$ or $\alpha = 0.01$. In this study, we prefer using the interpretation described in Collet (2003) that is summarised in Table 1. The same interpretation was used in Gatabazi and Kabera (2015), and Gatabazi et al. (2018, 2019e, 2020a).

Table 1. Evidence for or against H_0 based on comparing the p-value with the level of significance $\alpha = 0.05$.

p-Value (P)	Interpretation
$P > 0.1$	No evidence to reject the null hypothesis
$0.05 < P \leq 0.1$	Slight evidence against the null hypothesis
$0.01 < P \leq 0.05$	Moderate evidence against the null hypothesis
$0.001 \leq P \leq 0.01$	Strong evidence against the null hypothesis
$P < 0.001$	Overwhelming evidence against the null hypothesis

The log-rank test is better if proportional hazards can be assumed (Collet 2003). In such situation, the plots of survival functions do not cross one another. The Wilcoxon test is suitable when there is no proportional hazards assumption. Here, the survival curves of some groups cross one another (Collet 2003).

2.3. Cox Proportional Hazards Model (CPHM)

Assume p fixed covariates with values $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{ip})'$ for $i = 1, \ldots, n$ where n is the number of observations.

The CPHM is given by

$$h(t \mid \mathbf{x}_i) = h_0(t)\exp(\boldsymbol{\beta}'\mathbf{x}_i) \tag{1}$$

where $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_p)'$ is a p-dimensional vector of model parameters and and $h_0(t)$ is the baseline hazard function, that the hazard function when all the covariates are set to zero. The quantity

$$\psi_k = e^{\beta_k} \tag{2}$$

is called "*hazard ratio*", and is reported in applied studies as it is easier to interpret than the model parameters or log-hazard ratio $\beta_k = \ln \psi_k$ for $k = 1, \dots, p$ (Collet 2003).

Parameter estimation for model (1) with no tied events is conducted using partial likelihood introduced by Cox (1972).

Three approaches of approximating the partial likelihood in presence of tied event are suggested by Breslow (1974), Efron (1977) and Cox (1972). In practice, the three approximations of the partial likelihood function lead to similar results (Collet 2003). Many statistical packages, including STATA, provide options for using each of the above approximations. In STATA, Beslow is taken as the default.

2.4. Aalen Additive Hazards Model (AAHM)

The AAHM at time t of the ith of n individuals is given by

$$h[t \mid \mathbf{x}_i(t)] = \beta_0(t) + \beta_1(t)x_{i1}(t) + \beta_2(t)x_{i2}(t) + \ldots + \beta_p(t)x_{ip}(t) \tag{3}$$

where $\boldsymbol{\beta}(t) = \big(\beta_0(t), \beta_1(t), \dots, \beta_p(t)\big)'$ is the vector of parameter functions that may be estimated and $\mathbf{x}_i(t) = \big(x_{i1}(t), x_{i2}(t), \dots, x_{ip}(t)\big)'$ is the vector of covariates. The parameter function $\beta_0(t)$ is the baseline hazard function, that is the hazard when all the covariate functions are set to zero.

Aalen et al. (2008, p. 157) argue that, for computation stability, estimation in model (3) should be based on the cumulative parameter functions

$$B_k(t) = \int_0^t \beta_k(v)dv, \tag{4}$$

$k = 0, 1, 2, \dots, p$. Clearly, if $\beta_k(t)$ is constant, say $\beta_k(t) = \beta_k$, then

$$B_k(t) = \int_0^t \beta_k dv = \beta_k t \ \text{ which is represented by a straight line.}$$

Proposition 1. *Let*

$$Y_i(t) = \begin{cases} 1, & \textit{if individual } i \textit{ is at risk at time } t \\ 0, & \textit{otherwise.} \end{cases}$$

Assume that $dN_i(t)$ and $dM_i(t)$ are respectively a response variable and a random error terms of the ith individual. Model (3) *leads to the form*

$$dN_i(t) = \sum_{k=0}^{p} Y_i(t)x_{ik}(t)dB_k(t) + dM_i(t) \tag{5}$$

where $x_{i0} = 1$.

The proof of Proposition 1 can be found for example in Gatabazi et al. (2020b).

Thus, Model (5) has the form of a multiple linear regression model for the ith individual with covariates $Y_i(t)x_{ik}$ and parameters $dB_k(t)$ for $k = 0, 1, 2, \dots, p$ and $i = 0, 1, 2, \dots, n$.

Model (5) can be written in matrix form as

$$d\mathbf{N}(t) = \mathbf{X}(t)d\mathbf{B}(t) + d\mathbf{M}(t) \tag{6}$$

where

$d\mathbf{N}(t)$ is the $n \times 1$ vector of observations $dN_i(t)$
$\mathbf{X}(t)$ is the $n \times (p+1)$ design matrix with ith row given by $Y_i(t), Y_i(t)x_{i1}(t), \ldots, Y_i(t)x_{ip}(t)$
$d\mathbf{B}(t) = \left(dB_0(t), dB_1(t), \ldots, dB_p(t)\right)'$ is the $(p+1) \times 1$ vector of parameter functions
$d\mathbf{M}(t)$ is the $n \times 1$ vector of martingales (error terms) each with mean zero.

It follows from (6) and from the theory of least square estimation that if $\mathbf{X}(t)$ is of full rank, that is $[\mathbf{X}(t)]'\mathbf{X}(t)$ is non singular, then the ordinary least squares estimator of $d\mathbf{B}(t)$ is

$$d\widehat{\mathbf{B}}(t) = \left[(\mathbf{X}(t))'\mathbf{X}(t)\right]^{-1}(\mathbf{X}(t))'d\mathbf{N}(t) \tag{7}$$

If $\mathbf{X}(t)$ is not of full rank, then $d\mathbf{B}(t)$ is not estimable unless some constraint is imposed. However, most of current statistical packages have built-in routines to deal with matrices that are not of full rank and provide robust estimates of model parameters. The estimator $\widehat{\mathbf{B}}(t)$ obtained by integrating both sides of Equation (7) with respect to t is

$$\begin{aligned} \widehat{\mathbf{B}}(t) &= \int_0^t \left[(\mathbf{X}(t))'\mathbf{X}(t)\right]^{-1}(\mathbf{X}(t))'d\mathbf{N}(t) \\ &= \sum_{t_j \le t} \left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1}(\mathbf{X}(t_j))'\mathbf{y}_j \end{aligned} \tag{8}$$

where $\mathbf{y}_j$ is $n \times 1$ vector of zeros except the jth component equals to unit if the jth individual observes an event at time t_j (Aalen et al. 2008, p. 158; Hosmer and Royston 2002). Furthermore, the variance-covariance matrix of $\widehat{\mathbf{B}}(t)$ is

$$\mathrm{Var}\left[\widehat{\mathbf{B}}(t)\right] = \sum_{t_j \le t} \left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1}(\mathbf{X}(t_j))'\mathbf{D}(t_j)\mathbf{X}(t_j)\left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1} \tag{9}$$

where $\mathbf{D}(t_j)$ is an $n \times n$ diagonal matrix with elements y_j on the main diagonal (Aalen et al. 2008, p. 158; Hosmer and Royston 2002). The derivation of results (9) from (8) is easy to understand. In fact if two random vectors of variables $\mathbf{X}$ and $\mathbf{Y}$ are linked by $\mathbf{Y} = \mathbf{AX}$, where $\mathbf{A}$ is a matrix, then

$$\mathrm{Var}(\mathbf{Y}) = \mathbf{A}\,\mathrm{Var}(\mathbf{X})\,\mathbf{A}'$$

(Mulaik 2009).

As described in Hosmer and Royston (2002), if the vector of cumulative parameter coefficients at time t is estimated by (8), and its variance-covariance matrix by (9), then the estimator of the model vector of parameters at time t_j is

$$\hat{\boldsymbol{\beta}}(t_j) = \left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1}(\mathbf{X}(t_j))'\mathbf{y}_j \tag{10}$$

and

$$\mathrm{Var}\left[\widehat{\boldsymbol{\beta}}(t_j)\right] = \left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1}(\mathbf{X}(t_j))'\mathbf{D}(t_j)\mathbf{X}(t_j)\left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1}. \tag{11}$$

Aalen et al. (2008, p. 159) showed that the cumulative parameter function estimator $\hat{\mathbf{B}}(t)$ has approximately a multivariate normal distribution around its true value $\mathbf{B}(t)$, with the variance-covariance matrix expressed in (9). Therefore, the $100(1-\alpha)\%$ confidence interval for the kth cumulative parameter functions $B_k(t)$ is expressed by

$$\widehat{B}_k(t) \pm z_{\frac{\alpha}{2}} \sqrt{\hat{\sigma}_{kk}(t)} \tag{12}$$

where $\hat{\sigma}_{kk}(t)$ is the kth diagonal element of the variance-covariance matrix expressed in the Equation (9). To test that a covariate X_k has no significant effect on the hazard function given in model (3), Aalen et al. (2008) formulated the null and alternative hypotheses in the usual way as follows

$$H_0 : \beta_k(t) = 0,\ \forall\, t \in [0, t_0]$$

versus

$$H_1 : \beta_k(t) > 0 \text{ or } \beta_k(t) < 0$$

where t_0 is a suitably chosen time point, but often t_0 is the upper limit of the study time interval. If H_0 is true, then the increment $\Delta\hat{B}_k(t_j)$ at time t_j of the cumulative parameter function given in (8) tends to fluctuate around zero (Aalen et al. 2008). Under the alternative hypothesis $H_1 : \beta_k(t) > 0$, the increment $\Delta\hat{B}_k(t_j)$ tends to be positive while under $H_1 : \beta_k(t) < 0$, the increment $\Delta\hat{B}_k(t_j)$ tends to be negative. Furthermore if $\widehat{B}_k(t)$ approximately follows a straight line, then $\beta_k(t)$ is constant. The test described above is helpful when the estimated cumulative parameter functions are plotted against time. However, a quantitative measure of significance may be needed to assess the magnitude of significance. Hosmer and Royston (2002) advised to proceed as follows. Consider model (3) and assume that there is a need to test the null hypothesis

$$H_0 : \beta_k(t_j) = 0 \text{ for all } k \text{ with } k = 0, 1, \ldots, p. \tag{13}$$

Hosmer and Royston (2002) stated that the $(p+1)$ statistics for the above hypothesis are obtained from the components of the vector

$$\hat{\mathbf{u}} = \sum_{t_j} \mathbf{K}_j \hat{\boldsymbol{\beta}}(t_j) \tag{14}$$

where $\hat{\boldsymbol{\beta}}(t_j)$ given by (10) is the vector of estimators of the parameter coefficients for model (3), and $\mathbf{K}_j$ is a $(p+1) \times (p+1)$ diagonal matrix of weights. Four types of weights can be used.

- Weights 1: $\mathbf{K}_j = \text{diag}(1)$, that is $\mathbf{K}_j$ is a diagonal matrix with each element of the main diagonal equals to unit.
- Weights 2: $\mathbf{K}_j = \text{diag}(n_j)$ where n_j is the number of individuals at risk at time t_j.
- Weights 3: $\mathbf{K}_j = \text{diag}\left[\widehat{S}_{KM}(t_{j-1})\right]$ where $\widehat{S}_{KM}(t_{j-1})$ is the Kaplan–Meier estimate of the survival function at time t_{j-1} for $j = 2, 3, \ldots$ and $\mathbf{K}_1 = \text{diag}\left[\widehat{S}_{KM}(t_0) = 1\right]$.
- Weights 4: $\mathbf{K}_j = \text{diag}\left[\widehat{S}_{KM}(t_{j-1}) / \text{se}(\hat{\beta}_{kk}(t_j)\right]$ where $\hat{\beta}_{kk}(t_j)$ is the kth diagonal element of the variance-covariance matrix (11). Hence, $\mathbf{K}_j$ is a diagonal matrix whose main diagonal elements are the ratio of the Kaplan–Meier estimates of the survival function at time t_{j-1} and the standard error of the Aalen estimate of the parameter function of interest at time t_j.

To completely define the test statistic to use, the estimator of the variance-covariance matrix of $\hat{\mathbf{u}}$ given in (14) is obtained from the symmetric matrix $\mathbf{K}_j$ and the variance of $\hat{\beta}(t_j)$ given by (11). Hence,

$$\begin{aligned}\widehat{\mathrm{Var}}(\hat{\mathbf{u}}) &= \sum_{t_j} \mathbf{K}_j \mathrm{Var}\left[\hat{\boldsymbol{\beta}}(t_j)\right]\mathbf{K}_j' \\ &= \sum_{t_j} \mathbf{K}_j \left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1}(\mathbf{X}(t_j))'\mathbf{D}(t_j)\mathbf{X}(t_j)\left[(\mathbf{X}(t_j))'\mathbf{X}(t_j)\right]^{-1}\mathbf{K}_j'. \end{aligned} \tag{15}$$

Hence, the test statistic for H_0 given in (13) is

$$z_{u_k} = \frac{\hat{u}_k}{\mathrm{se}(\hat{u}_k)} \tag{16}$$

where $\hat{u}_k$ is the kth element of $\hat{\mathbf{u}}$ given in (14) and $\mathrm{se}(\hat{u}_k)$ is the square root of the kth diagonal element of $\widehat{\mathrm{Var}}(\hat{\mathbf{u}})$ given in (15). Hosmer and Royston (2002) pointed out that the statistic z_{u_k} in (16) approximately follows the standard normal distribution.

2.5. Dataset

Among over 6000 active and inactive cryptocurrencies, we recorded 500 cryptocurrencies whose information on the variables of interest is available. The details of other cryptoccurrencies is not available, and for many of them, the white papers are not decentralized. The covariates of interest are described in Table 2.

Table 2. Description of variables of interest.

Variable	Description	Code/Value/Unit
Type	The type of a cryptocurrency	0 = token 1 = coin
Blockchain	Indicator of the type of blockchain of a cryptocurrency	0 = other 1 = Ethereum 2 = Standalone
Series	Indicator on when a cryptocurrency was released	0 = series 1 (2009–2013) 1 = series 2 (2013–2017) 2 = series 3 (2017–2021)
Mining	Indicator on whether a cryptocurrency is minable or not	0 = not minable 1 = minable
Region	Region in which a cryptocurrency' s'headquarters are based	0 = unknown 1 = South America 2 = Oceania 3 = North America 4 = Europe 5 = Asia 6 = Africa

The Kaplan–Meir estimation of the overall survival function (Figure 1) at the end of the study time is 75%, or equivalently, the rate of death at the end of the study time is 25%. The time is in years with origin fixed in 2009.

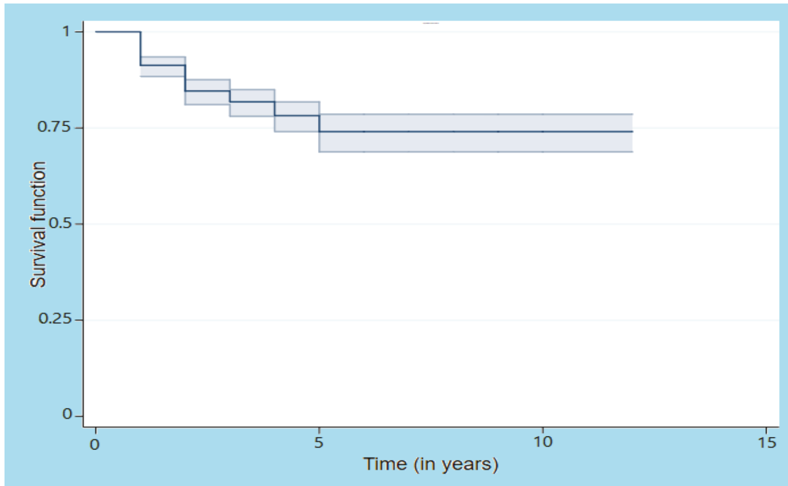


Figure 1. Kaplan–Meier estimates and 95% confidence limits of the survival function for the cryptocurrency data.

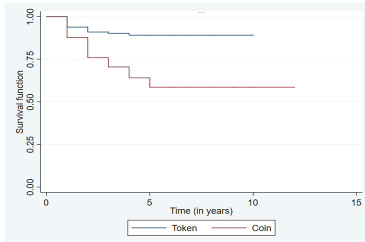
The survival outcomes of the levels of the variables can be compared graphically by using the Kaplan–Meier estimation of the survival function per group of covariate. The plots are displayed in Figure 2. The log-rank and Wilcoxon test statistics are summarized in Table 3.

Figure 2a suggests that the survival outcome is significantly better for tokens as compared to coins ($\chi^2 = 42.02;\ \ p < 0.001$). Figure 2b indicates a relatively better survival outcome for cryptocurrencies under Ethereum ($\chi^2 = 66.90;\ \ p < 0.001$). Figure 2d suggests a significant high risk as a cryptocurrency is minable ($\chi^2 = 32.22;\ \ p < 0.001$). Among the levels of the variable *Series*, cryptocurrencies released in the series 2009–2013 present significantly better survival outcomes ($\chi^2 = 8.04;\ \ p = 0.018$) as Figure 2d indicates, this is the same for South American cryptocurrencies ($\chi^2 = 132.03;\ \ p < 0.001$) as Figure 2e shows of the variable *Region*.

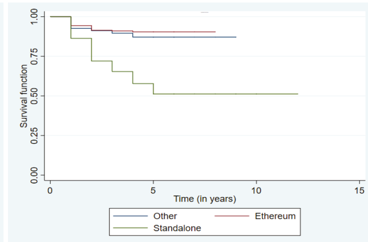
Table 3. Log-rank and Wilcoxon test statistics.

Variable	Log-Rank χ^2 Test Statistic (p-Value)	Wilcoxon χ^2 Test Statistic (p-Value)
Type	42.02 ($p < 0.001$)	35.45 ($p < 0.001$)
Blockchain	66.90 ($p < 0.001$)	55.62 ($p < 0.001$)
Mining	32.22 ($p < 0.001$)	22.34 ($p < 0.001$)
Series	13.10 (0.001)	8.04 (0.018)
Region	153.49 ($p < 0.001$)	132.03 ($p < 0.001$)

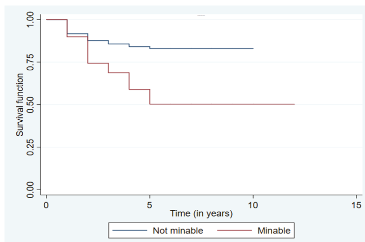
The log-rank test for comparison is suitable for comparing levels of covariates that obey the proportional hazard assumption (PHA); these are covariates *Type*, *Blockchain* and *Mining* for which the plots are approximately parallel. Wilcoxon test is suitable in comparing the levels of covariates *Series* and *Region* for which corresponding plots cross each other, leading to the violation of the PHA.



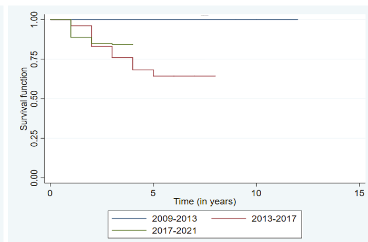
(**a**)



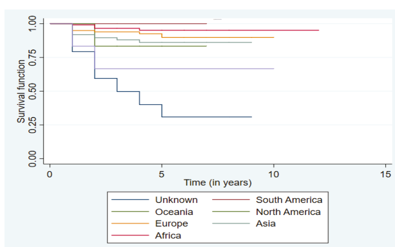
(**b**)



(**c**)



(**d**)



(**e**)

Figure 2. Plots of the Kaplan–Meier estimates of the survival function for levels of covariates from 2009 to 2021. (**a**) Type, (**b**) Blockchain, (**c**) Mining, (**d**) Series, (**e**) Region.

3. Results and Interpretation

3.1. Cox Proportional Hazards Model (CPHM)

Unlike Kaplan–Meier estimation, which treats one variable at a time, the the CPHM makes inference by considering several variables at a time.

Table 4 presents the estimated hazard ratios based on all the covariates.

The model suggests that the risk of death of cryptocurrencies under standalone blockchain is 2.771 (95% CI: 1.221; 6.288) times that of cryptocurrencies under the referral blockchain.

The significance for covariate *Region* is observed in North America, Europe and Asia. I all these regions the survival outcomes are better than the referral level. The CPHM suggests that the risk of death of cryptoccurrencies from unknown region is 6.757 (95% CI: [3.106; 14.706]) times that of cryptocurrencies based in North America. Such risk is 4.348 (95% CI: [2.439; 7.752]) times that of cryptocurrencies based in Europe and 13.333 (95% CI: [5.181; 34.483]) times that of cryptocurrencies based Asia.

Table 4. Cox Proportional hazards model for all covariates.

Covariate (Reference)	Level	Haz. Ratio	Std. Err.	z	P > z	95% Conf. Int.
Type (Token)	Coin	0.737	0.350	−0.640	0.521	[0.290; 1.872]
Blockchain (Other)	Ethereum	0.798	0.382	−0.470	0.638	[0.312; 2.041]
	Standalone	2.771	1.159	2.440	0.015	[1.221; 6.288]
Series (Series 1)	Series 2	3.270	0.230	2.840	0.671	[1.452; 3.215]
	Series 3	2.870	0.952	1.450	0.424	[1.413; 3.624]
Mining (Not minable)	Minable	0.855	0.208	−0.640	0.520	[0.530; 1.378]
Region (Unknown)	South America	0.091	0.396	−0.562	0.741	[0.067; 0.201].
	Oceania	0.402	0.414	−0.880	0.377	[0.053; 3.031]
	North America	0.148	0.059	−4.800	$p < 0.001$	[0.068; 0.322]
	Europe	0.230	0.068	−4.980	$p < 0.001$	[0.129; 0.410]
	Asia	0.075	0.036	−5.370	$p < 0.001$	[0.029; 0.193]
	Africa	0.755	0.554	−0.380	0.702	[0.179; 3.182]

3.2. Aalen Additive Hazards Model (AAHM)

Hosmer and Royston (2002) designed a STATA code based on an ado file for analysing survival data using the AAHM.

Figure 3a displays the cumulative parameter function with its 95% confidence limits for cryptocurrencies under Ethereum blockchain. The plot oscillates around the zero line, and the plot of 95% confidence limits are on either sides of the zero line. This indicates that the slope may be zero at some time value, and the risk of cryptocurrencies under Ethereum may not be significantly different from that of the referral group. The same AAHM results are observed for the crypto-coins (Figure 3c) and minable cryptocurrencies (Figure 3d).

Figure 3b indicates that the cumulative parameter function for cryptocurrencies under standalone blockchain is positive, and so is the major part of the 95% confidence limits. This suggests that the risk of such cryptocurrencies is higher than that of the referral group. The same observation occurred for cryptocurrencies released from the year 2013 as Figure 3e,f show.

Figure 4 gives the plots of the cumulative parameter functions and their 95% confidence limits for levels of the variable *Region*. The cumulative parameter functions with their 95% confidence limits are negative for levels *South America* (Figure 4a), *North America* (Figure 4c), *Europe* (Figure 4d) and *Asia* (Figure 4e). The pattern for level *Oceania* is negative together with the major parts of its confidence limits (Figure 4b). This suggests a relatively higher risk of cryptocurrencies of the referral region. The pattern for level *Africa* (Figure 4f) oscillates around the zero line, and the plot of 95% confidence limits are on either sides of the zero line. This indicates that the slope may be zero at some time value, and the risk of African cryptocurrencies may not be significantly different from that of the referral region.

Table 5 displays the results of the test statistics of the AAHM for all the covariates using the four types of weights. All the tests are against the difference of the levels of covariate *Mining*. The test based on type 4 weights suggests the moderate evidence of difference of the levels of covariate *Type* and the overwhelming difference of levels of covariates *Blockchain*, *Series* and *Region*. The overwhelming difference for levels of covariate *Series* and some levels of covariate *Region* is also noticed by test 1, 2 and 3.

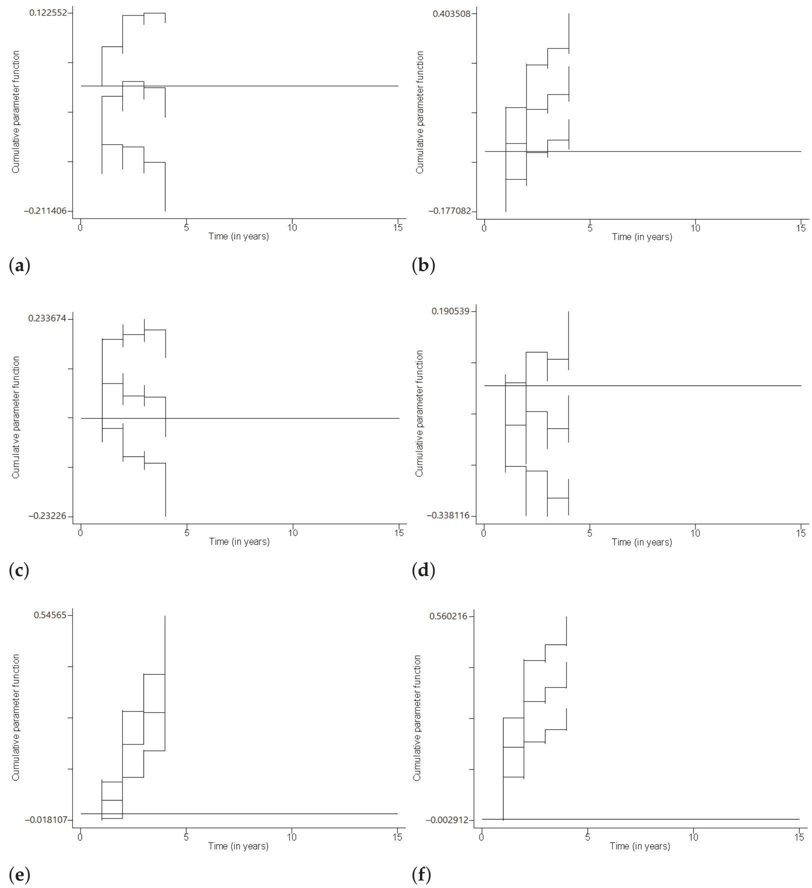


Figure 3. AAHM for levels of covariates *Type*, *Blockchain*, *Mining* and *Series*. (**a**) Ethereum, (**b**) Standalone, (**c**) Coin, (**d**) Minable, (**e**) Series 2 (2013–2017), (**f**) Series 3 (2017–2021).

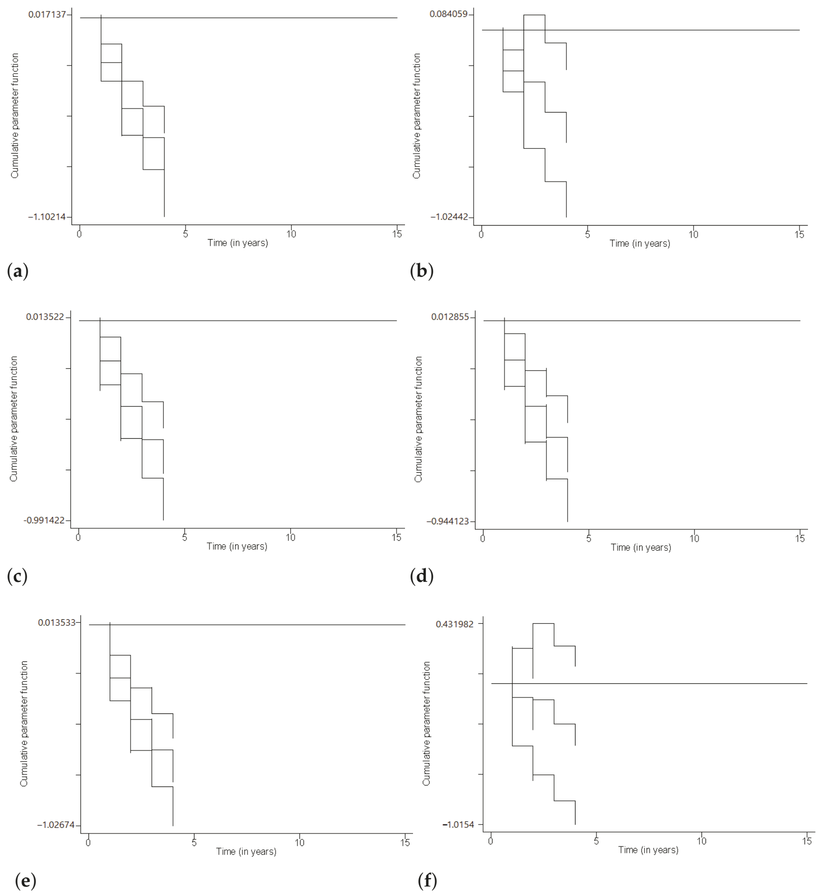


Figure 4. AAHM for levels of covariate *Region*. (**a**) South America, (**b**) Oceania, (**c**) North America, (**d**) Europe, (**e**) Asia, (**f**) Africa.

Table 5. Tests for significance of covariates.

		Test 1		Test 2		Test 3		Test 4	
Covariate (Reference)	**Level**	**z**	**P**	**z**	**P**	**z**	**P**	**z**	**P**
Type (Token)	Coin	−0.477	0.634	0.004	0.997	−0.385	0.700	−2.229	0.026
Blockchain (Other)	Ethereum	−0.451	0.652	−0.437	0.662	−0.510	0.610	7.230	$p < 0.001$
	Standalone	3.098	0.002	2.712	0.007	2.907	0.004	5.196	$p < 0.001$
Series (Series 1)	Series 2	6.114	$p < 0.001$	6.052	$p < 0.001$	6.090	$p < 0.001$	5.558	$p < 0.001$
	Series 3	6.519	$p < 0.001$	6.524	$p < 0.001$	6.526	$p < 0.001$	7.719	$p < 0.001$
Mining (Not minable)	Minable	−0.324	0.746	−0.754	0.451	−0.448	0.654	0.990	0.322
Region (Unknown)	South America	−7.367	$p < 0.001$	−7.784	$p < 0.001$	−7.487	$p < 0.001$	−7.365	$p < 0.001$
	Oceania	−2.956	0.003	−2.935	0.003	−2.984	0.003	−7.153	$p < 0.001$
	North America	−5.895	$p < 0.001$	−6.312	$p < 0.001$	−5.985	$p < 0.001$	−6.110	$p < 0.001$
	Europe	−5.332	$p < 0.001$	−5.661	$p < 0.001$	−5.403	$p < 0.001$	−5.497	$p < 0.001$
	Asia	−6.327	$p < 0.001$	−6.837	$p < 0.001$	−6.471	$p < 0.001$	−6.353	$p < 0.001$
	Africa	−1.468	0.142	−1.339	0.181	−1.418	0.156	−7.350	$p < 0.001$

4. Conclusions

This paper used survival regression models for analysing the risk to death of the cryptocurrencies from 2009 to Q2 2021. The dataset is a sample of 500 cryptocurrencies for which a correct information on the covariates of interest were found. The exploration was conducted using the Kaplan–Meier estimation of the survival function.

The Cox Proportional Hazards Model (CPHM) also was used and suggested a relatively higher risk for cryptocurrencies under standalone blockchain. This result was also found by the plot of the survival functions of the levels of blockchain covariate. It was found by the CPHM that cryptocurrencies released in the series 2013–2017 are at a high risk as compared to those of 2009–2013 release. The CPHM also suggested that cryptocurrencies for which headquarters are unknown are at a relatively higher risk. The results of the Aalen Additive Hazards Models (AAHM) showed that unlike other covariates, the levels of covariate *Mining* are not significantly different.

Among more than 6000 active and inactive cryptocurrencies, this paper considered 500 cryptocurrencies for which the information on the variables of interest were easily found. The study still needs improvement by considering a relatively bigger sample size. Apart from considering a big sample in future research, re-sampling may also improve the measurement of the standard errors and then evaluate the accuracy of the results found in this paper.

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Article

The Impact of Commodity Price Shocks on Banking System Stability in Developing Countries

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Abstract: This study examines the impact of commodity price shocks on the banking sector stability of 18 African commodity-exporting economies using an unbalanced panel dataset spanning a 16-year period from 2000–2015. The study on the impact of commodity price shocks on African commodity-exporting economies' banking sectors was estimated using a panel fixed effects model. The empirical findings indicate that commodity price shocks increase bank credit risk (non-performing loans) and, thus, pose a risk to the banking sector stability of African commodity-exporting economies. The results for the disaggregated shocks reveal that both positive and negative shocks weaken banking sector stability. In addition, commodity price shocks are discovered to decrease credit extension to the private sector, highlighting an additional channel through which the impact of commodity price shocks may be perpetuated to the real economy.

Keywords: commodity price shocks; banking sector stability; panel data; Africa

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1. Introduction

African countries are highly dependent on commodities; this exposes them to risks of economic, political, and financial instability (Christensen 2016). The economic and political implications of commodity dependence are well-rooted in the literature, with a plethora of research focusing on how it impacts economic growth, debt, conflict, and financial development (Hamilton 1983, 2009; Deaton and Miller 1995; Lescaroux and Mignon 2008; Kilian et al. 2009; Rafiq et al. 2016; Montfort and Ouedraogo 2017; Bangara and Dunne 2018). Limited research has examined the possible impact of commodity price shocks on financial sector stability, specifically on banking sector stability (Alodayni 2016; Kinda et al. 2016; Agarwal et al. 2017; Eberhardt and Presbitero 2018). Commodity price shocks affect the corporate, household, government, and banking sectors of the economy (Christensen 2016). The banking sector may, therefore, be an additional channel through which the impact of commodity price shocks is perpetuated to the real economy.

African economies are mainly dominated by large domestic and foreign banks (Chironga et al. 2018), and as such, banking stability (or instability) can play a significant role in lessening (or intensifying) the impact of commodity price shocks on the macroeconomy (Poghosyan and Hesse 2009; Miyajima 2016; Kooros and Semetesy 2016; Alodayni 2016; Kinda et al. 2016). For example, the 1980s and 1990s comprised extensive banking crises, with most of the instability concentrated in commodity-exporting economies (Eberhardt and Presbitero 2018). Few African economies experienced banking crises during this period. According to Eberhardt and Presbitero (2018), factors such as long periods of economic growth, financial deepening, and high and stable commodity prices contributed to the resilience of African banking sectors. Structural reforms for sound macroeconomic policies and improved regulatory frameworks have further supported African banking sectors (Caggiano et al. 2013; Bangara and Dunne 2018). Despite this resilience, macroeconomic and banking sector vulnerabilities are clearly still in place and are likely to emerge as financial deepening increases and as the financial system becomes more complex. In

2014–2015, several economies began experiencing financial distress, indicated by declining bank profitability and deteriorating asset quality (UNDP 2016; IMF 2017). Even though the country-specific problems faced by these countries may have contributed to the financial distress, the sharp and persistent decline of commodity prices has certainly perpetuated the issue for commodity-exporting economies (see Figure 1).

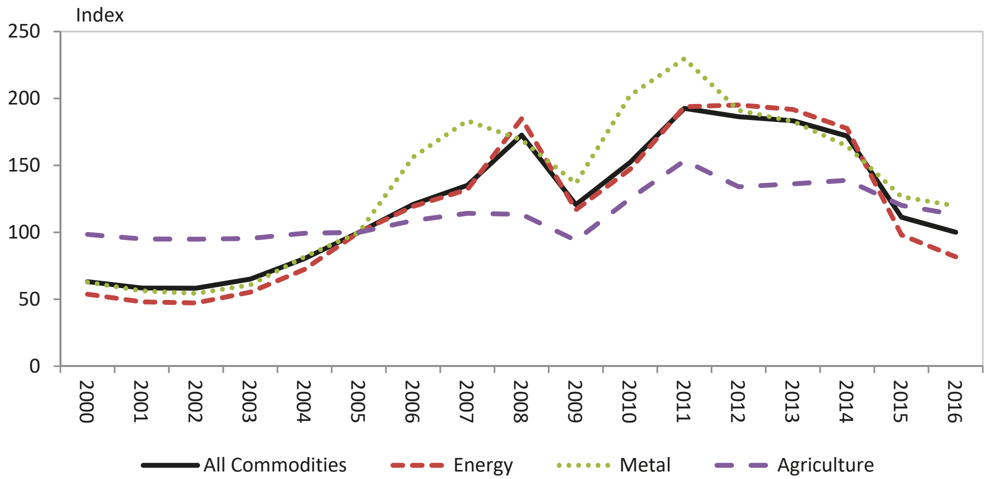

Figure 1. Commodity price indices (2005 = 100). **Source**: Author's own presentation using IMF data.

Given these developments and considerations, this study examines the vulnerability of the banking sectors of 18 African countries to commodity price shocks. The analysis covers the period spanning 2000 to 2015. The dependence of African economies on commodity exports has long been debated and analyzed. Even though most African countries benefit from commodity price booms, commodity price busts remain a concern due to their magnitude and duration. Commodity price volatility may not be avoided, but countries can ensure that they are not largely impacted by diversifying and reducing their commodity dependence. There is clear consensus on the impact of commodity price shocks on macroeconomic factors. Limited research has focused on how the banking sectors of African economies are impacted. There is a need to examine whether the banking sector may be an additional channel through which commodity price shocks impact the real economy. The 2007–2008 GCF brought to light the pieces that were missing in maintaining financial sector stability. The close link between commodity markets and the banking sector (Kinda et al. 2016), therefore, supports the need to understand how the financial sector is impacted by commodity price shocks. This study contributes to the literature in three key ways. First, the study emphasizes the role of commodity price shocks in triggering banking sector instability. In a related paper, Kinda et al. (2016) showed that commodity price shocks are associated with financial sector fragility in developing countries. Kinda et al. (2016) limited the focus of their study, focusing only on minerals, fuels, and metals. This study extends the research by Kinda et al. (2016) by focusing on most commodity groups. Second, while previous studies have focused on advanced, emerging, developing (not just African), and low-income countries, this study examines the experience of only African commodity-exporting countries. This is specifically relevant because of the financial sector vulnerabilities that were revealed in African countries following the 2015 commodity price decline. African economies' exposure to and dependence on commodity prices increased financial sector vulnerabilities in these countries (Eberhardt and Presbitero 2018). Third, while Kinda et al. (2016) outlined how the financial sector responds to both negative and positive shocks, this study examines this relationship using overall positive and negative shocks. Further, the study contributes to the extant literature by emphasizing the differences in commodity price asymmetries between various commodity groups. To the best of the author's knowledge, the only work that emphasized this relationship was Addison et al. (2016).

Employing a panel fixed effects (FE) model, the results of the study indicate that commodity price shocks weaken banking sector stability through increasing bank credit risk (NPLs). More specifically, a one-unit increase[1] in the commodity price shock increases bank credit risk by 0.381%, which is in line with previous studies (Kinda et al. 2016). When disaggregated by positive and negative commodity price shocks, the results reveal that both positive and negative commodity price shocks weaken banking sector stability and that positive shocks, surprisingly, have the greatest impact on banking sector stability. The lack of asymmetry is in line with Addison et al. (2016), who found, using a similar commodity price shock measure, that positive and negative agricultural commodity price shocks in sub-Saharan African countries did not necessarily respond differently. Finally, the estimation of the impact of commodity price shocks on bank lending[2] shows that commodity price shocks do indeed decrease bank lending, which is in line with Agarwal and colleagues (2017). As a matter of fact, negative mineral, fuel, metal, and chemical price shocks have substantive negative implications on bank lending in African countries. Given these findings, this study deduces that commodity price shocks do not only have an impact on banking sector stability (which can be perpetuated to the real economy) but also have a direct impact on bank lending as a means of economic growth and development (Greenwald and Stiglitz 1991, 2003).

The remainder of the study is divided as follows. Section 2 briefly discusses the channels through which commodity price shocks can impact the economy and the banking sector. Section 3 reviews the theoretical and empirical literature. Section 4 defines the data, model specification, and estimation techniques. Section 5 presents the results, and Section 6 provides the main conclusions.

2. Commodity Price Shocks—Transmission Mechanism

Economic relationships are hardly ever clear and direct. This is no different when trying to understand and examine the relationship between commodity price shocks and banking sector stability. In order to unpack this, the various transmission channels through which commodity price shocks may impact the economy (with a specific focus on how the banking sector is impacted) are briefly discussed. *To be specific, the macroeconomic, fiscal, exchange rate, and banking channels are discussed. Further, the scenario discussed below is based on the assumption of a decline in commodity prices. One would expect the opposite deductions in the case of an increase in commodity prices.*

<u>Macroeconomic channel:</u> Following a fall in commodity prices, economies usually experience a decline in exports, investment, and output. Declining exports, investment, and output weigh on the corporate and household sectors. Exports decline and, thus, economies fail to generate as much export revenue as is generated during periods of higher commodity prices. Investment in commodity extraction and supporting industries weakens, impacting not only actual output but also potential output (Christensen 2016). Several authors have established a negative relationship between commodity price shocks and economic growth (Deaton and Miller 1995; Dehn 2000; Karl 2004; Bruckner and Ciccone 2010; Hammond 2011; Christensen 2016). African commodity exporters experience economic growth averaging 5% each year. A reversal of this growth was witnessed following the commodity price crash that began in late 2014 (Ighobor 2016). For example, Nigeria's oil revenue accounts for approximately 90% of its export revenue; as a result of the decline in commodity prices, its revenue declined substantially, and the country's economic growth moderated from 5.4% in 2014 to 2.9% in 2016 (Ighobor 2016). Low growth can impact firms', governments', and consumers' ability to service their bank debts, which, in turn, exposes the banking sector to credit risk. In line with a fall in commodity-exporting firm production and, thus, revenue, unemployment may rise, leaving households at risk in an already vulnerable economic environment (Blanchard and Gal 2008). Vulnerable firms and individuals means a greater

risk of defaulting on payments, impacting bank balance sheets and, through contagion[3], the greater banking system (Makri et al. 2014).

Fiscal channel: African commodity-exporting countries rely heavily on commodity export revenue to boost and support economic growth and development. The commodity export proceeds of some countries in Africa account for more than 70% of the national budget (Alesina et al. 2008; UNDP 2015; Christensen 2016; Ighobor 2016). This reliance means that negative commodity price shocks can certainly decrease fiscal performance (Spatafora and Samake 2012; Kinda et al. 2016). A decline in export revenue causes a decline in government revenue (and, thus, a decline in government expenditure) of commodity-dependent economies. Kinda et al. (2016) reiterated this by saying that commodity price shocks reduce tax revenue, worsen terms of trade, increase fiscal deficits, and decrease the competitiveness[4] of government-dependent institutions. Governments also borrow from the banking sector, so a reduction in government revenue will also impact their ability to service their bank (and other) debts. Commodity price shocks can, therefore, also pose a banking stability risk through the weakening of fiscal performance.

Exchange rate channel: It is also important to note that, as commodity exporters, African economies encounter two possible scenarios: first, increasing foreign exchange reserves as a result of higher prices or, second, decreasing foreign exchange reserves due to lower commodity prices. A substantial decline in commodity prices can increase fiscal deficits and impact exchange rate reserves. This may influence the government and domestic banks to borrow internationally to withstand domestic economic conditions brought on by commodity price shocks. In turn, this increases the foreign-denominated debt of both agents (Kinda et al. 2016). Any sudden and substantial depreciation of the domestic currency or increase in international interest rates increases the vulnerability of the banking sector and, thus, impacts its stability.

Banking channel: African countries' dependence on commodities may also have a direct impact on the banking system. First, commodity dependence structures the bank lending channel in ways which can create 'system risk' not just for the banking system but also for the greater financial system (Christensen 2016). As witnessed during the 2007–2008 global financial crisis (GFC), banks freely extend credit during periods of economic and financial boom. Similarly, during periods of commodity boom, domestic credit extension grows, with banks extending credit even to the less creditworthy. Credit extension is important for growth and development, but rapid and extensive credit growth can seriously impact the stability of the financial system. Second, previous research indicated that commodity exporters held savings as a precautionary measure to address the volatile nature of commodity prices (Bems and Filho 2011). "If the windfalls are saved in domestic banks, this could threaten the banking sector in case of negative shocks that could lead to sizeable withdrawals" (Kinda et al. 2016; Christensen 2016). Challenges in one bank can spread to other banks; this can result in bank runs[5] with the potential to completely destabilize the financial system. There were several bank runs during the 2007–2008 GFC, and the linkages between banks and financial institutions resulted in contagion, impacting the stability of the entire international financial system.

3. Literature Review

A theoretical model underpinning the analysis on the determinants of credit risk is the financial accelerator theory. This theory posits that endogenous developments in the credit markets propagate shocks to the real macroeconomic environment (Bernanke et al. 1999). The theory posits that credit shock is amplified through information asymmetries between lenders and borrowers and through a balance sheet effect. Credit risk is one of the largest risks faced by banks. As such, several studies have focused on the implications of credit risk on the banking system (Mpofu and Nikolaidou 2018).

During periods of commodity price boom, banks generate a lot of liquidity, which makes them more lax in their lending (Ftiti et al. 2016). Thus, banks may increase lending during commodity price booms, but the opposite may hold during commodity price busts, resulting in both a reduction in credit extension and a deterioration in loan quality. This notion is supported by Ftiti et al. (2016), who analyzed the relationship between the commodity price cycle and credit cycle in three commodity-exporting African economies. Their findings indicated that the credit market is sensitive to persistent commodity price shocks. Kablan et al. (2017), who used a sample of African commodity-exporting countries, established similar results showing a positive relationship between commodity price booms and credit growth. Kablan et al. (2017) also emphasized that a commodity boom reversal affects both the macroeconomic and financial sectors, decreasing commodity exporters' capacities to service their debts. Knock-on effects increase NPLs and weigh on banking sector stability, which, in African economies, eventually impacts the entire financial system. The findings of Kablan et al. (2017) are crucial given the volatility and uncertainty related to commodity prices. The views of both Ftiti et al. (2016) and Kablan et al. (2017) are in line with Cashin and McDermott (2002), who established that African economies' commodity dependence makes them sensitive to lending booms and, thus, rising NPLs.

Most of the literature related to this study has focused specifically on oil prices. For example, Miyajima (2016), with evidence from Saudi Arabia and using generalized method of moments (GMM) and panel vector autoregression (PVAR) methods, indicated that low oil prices and non-oil GDP led to a rise in NPLs. In turn, this transmitted to the balance sheets of banks through weak macroeconomic variables. This is in line with Alodayni (2016), who focused on the oil–macrofinancial linkages in the Gulf Cooperation Council countries (GCC) region. The study, also employing a panel GMM and PVAR model, on 24 GCC banks during the period 2000 to 2014 established that oil prices, along with other macroeconomic variables, have an impact on NPLs and that higher NPLs have adverse effects on GCC economies. Al-Khazali and Mirzaei (2017) also established related results when they analyzed the impact of oil price movements on the NPLs of 30 oil-exporting countries over the period 2000 to 2014 using panel GMM. Their results revealed three things: first, that a rise (or fall) in oil prices leads to a decrease (or increase) in the NPLs of oil-exporting economies; second, that oil price shocks have asymmetric effects on bad loans (NPLs), and finally, that the negative impact of adverse oil price shocks has greater implications for the loans of large banks. These findings are significant considering that the banking sectors in developing countries (specifically African countries), dominate the financial sector (Allen et al. 2011). Any vulnerability in the banking sector, therefore, places the whole system at risk. Kooros and Semetesy (2016) assessed the relationship between international oil prices and the financial system in GCC countries. Their analysis incorporated data for 42 GCC banks spanning from 2000 to 2014. The study employed a system GMM technique and a PVAR model to assess the macroeconomic and bank-specific determinants of NPLs and the feedback loops between macroeconomic and bank balance sheet variables, respectively. In the first place, the study established that bank asset quality (NPLs) is impacted by oil prices and macroeconomic variables; second, the study also established feedback loops between oil price movements and bank balance sheets, emphasizing the notion that instability in the banking sector results in unwanted economic consequences for the real sector.

The closest literature to this empirical study comes from Kinda et al. (2016) and Eberhardt and Presbitero (2018). Kinda et al. (2016) examined how commodity price shocks impact financial sector fragility by focusing on 71 commodity-exporting emerging and developing economies for the period of 1997 to 2013. The study employed a panel fixed effects model to estimate the effect of commodity price busts on financial soundness indicators[6]. The results revealed that commodity price shocks weaken the financial sector and that larger shocks have a greater impact on financial sector stability. The study then went on to analyze a banking crisis using a conditional fixed effects logit model; the results of this estimation indicated that commodity price shocks are associated with banking crises. Eberhardt and Presbitero (2018) developed an empirical model to predict the relationship between commodity price movements and banking crises on a sample of 60 low-income countries (LICs) over the period of 1981 to 2015. The authors employed a random effects Mundlak logit model in their estimation. Their results are in line with the findings from Kinda et al. (2016), showing that commodity price movements are an economically substantial and robust driver of banking crises in LICs. These findings are in line with Kaminsky and Reinhart (1999), who provided evidence for how instability in the banking sector can trigger a financial crisis. The study found, using a sample of emerging market economies, that risk in the banking sector leads to a currency crisis. The authors indicated that, when and if a currency crisis deepens, it spreads to the entire economy. In the empirical literature, the studies of Rudolf et al. (2021), Doumenis et al. (2021), and Sami and Abdallah (2022), among others, have highlighted the importance of digital commodities (such as Bitcoin and cryptocurrency), but given that this study is not focused on the impact of digital commodities on banking systems in Africa, we paid less attention to the review of previous studies focusing on digital commodities and the effect they have on banking systems of African countries. While most of the empirical literature on the linkages between commodity price shocks and credit risk has focused specifically on oil price shocks, this study adds to the current limited research by considering all commodities. Including all commodities broadens the scope of the research and, thus, allows for a more comprehensive analysis. The paper closest to this study, Kinda et al. (2016), focused only on fuel, mineral, and metal commodities. This study is also motivated by Kinda et al. (2016) focusing on emerging and developing countries, without isolating African economies. African economies are isolated in this study because of their dependence on commodity exports and the potential vulnerability their banking sectors could encounter because of commodity price shocks. This study further expands on the previous literature by examining how the various commodity groups impact the banking sector and how they impact bank credit extension.

4. Data and Methodology

4.1. Methodology

Several equations were estimated to analyze the relationship between commodity price shocks and banking sector stability. This study adopted a model similar to that employed by Kinda et al. (2016). Panel data was characterized by observations of multiple phenomena which were obtained over multiple periods of time. The characteristics of the panel data were synonymous to the data sample used in this study, making panel analysis the most appropriate technique (Kinda et al. 2016). More specifically, the panel fixed effects[7] econometric model was employed because each country included in the sample had its own unique set of economic, political, and institutional characteristics that could be correlated with the explanatory variables. The panel fixed effects technique controlled these country-specific effects and prevented biased estimates.

Related studies, such as Alodayni (2016), Kooros and Semetesy (2016), and Al-Khazali and Mirzaei (2017), have opted to employ a system generalized method of moments (SGMM) technique. It is a system estimator that combines the regressions in differences and levels, resulting in consistent estimates of the parameters of interest. The consistency of this model, however, depends on the validity of the moment conditions (Arellano and Bover 1995). The Sargan[8] test of over-identified instruments was employed to test the overall validity of the instruments and, thus, the consistency of the model. The null hypothesis was rejected, rendering the SGMM an inappropriate method for this study. As a result, the FE model was employed. The equations that were estimated are shown below.

The baseline model estimated the effect of the overall commodity price shocks on banking sector stability. The empirical specification takes the following general form:

$$NPL_{it} = \beta_0 + \beta_1 CPS_{it} + \sum \gamma_K X_{i,tK} + \sum \gamma_{Km} Z_{i,tm} + \varepsilon_{it} \quad (1)$$

where NPL_{it} represents the banking sector stability variable (non-performing loans). CPS_{it} represents the commodity price shock variable. $\sum \gamma_K X_{i,tK}$ and $\sum \gamma_{Km} Z_{i,tm}$ represent the vectors of the banking specific and macroeconomic control variables, respectively, and, finally, ε_{it} represents the error term, including country-specific fixed effects and an idiosyncratic term.

Equation (1) was re-estimated using a positive and a negative commodity price shock. These shocks were derived from the overall commodity price shock equation:

$$NPL_{it} = \beta_0 + \beta_1 CPSpos_{it} + \sum \gamma_K X_{i,tK} + \sum \gamma_{Km} Z_{i,tm} + \varepsilon_{it} \tag{2}$$

$$NPL_{it} = \beta_0 + \beta_1 CPSneg_{it} + \sum \gamma_K X_{i,tK} + \sum \gamma_{Km} Z_{i,tm} + \varepsilon_{it} \tag{3}$$

where all other variables remain as in (1), while $CPSpos_{it}$ and $CPSneg_{it}$ represent positive and negative commodity price shocks, respectively.

The equations for the disaggregated commodity groups (agriculture, minerals, fuels, metals, and chemicals) were estimated using the same equations.

4.2. Data

An unbalanced panel dataset of 18 commodity-exporting African countries and the list of commodities can be found in Tables A1 and A2, respectively. The dataset comprised bank-specific financial stability indicator (FSI) (IMF 2006), macroeconomic, and commodity data for all the countries in question. The data period of 2000 to 2015 captured the commodity price bust (and the 2007–2008 GFC) that occurred in 2007–2008 and the recent 2014–2015 one. The bank-specific FSI data were sourced from the Federal Reserve Economic Data (FRED) of St. Louis and from the World Bank (WB) Global Financial Development databases. The macroeconomic (control variables) data were compiled using data from the World Bank Global Financial Development database and the IMF. The United Nation (UN) Comtrade database served as the source for the disaggregated commodities data.

The variables were defined as follows: the main dependent variable was non-performing loans (NPLs). It was a ratio of NPLs to total loans and was employed as a measure of credit risk in the study. Domestic credit extension was also employed as a dependent variable when estimating the impact of commodity price shocks on bank lending.

A number of independent variables were included in the study. The bank specific variables of profitability, capital adequacy, and liquidity were some of the variables used as financial stability indicators (IMF 2006). This is in line with studies, such as Kinda et al. (2016) and Eberhardt and Presbitero (2018), that used these variables, alongside others, as determinants of banking sector fragility and banking crises, respectively. In essence, the banking sector variables acted as proxies for a country's financial sector position.

The study also considered variables that could act as proxies for macroeconomic policy sustainability and stabilization issues, as well proxies for monetary and fiscal policy. The macroeconomic variables included economic growth, inflation, and unemployment. The monetary policy proxy variables included change in the exchange rate, real interest rate, M2 over external reserves, and domestic savings. Government revenue was employed as the fiscal policy proxy. These variables, as well as their expected priori, are summarized in Table A3.

There are various approaches through which commodity price shocks have been quantified in the literature. This study adopted the real commodity price change measure as a proxy for commodity price shocks (Mork 1989; Poghosyan and Hesse 2009). The commodity price shock measure in this study was computed per country, per time period (annual), and per commodity. The real commodity price measure is indicated below:[9]

$$cps_t = \frac{\sum_{i=1}^{365} \min[0, \log(p_t) - \min[\log(p_{t-1})]] * 100}{365} \tag{4}$$

where cps_{it} is the commodity price shock for country i at time t; p_{it} is the commodity export revenue in the current period; and p_{it-1} is the commodity export revenue in the preceding period. Cps_{it}, therefore, simply measures the annual commodity price shock for every country and each commodity included in the study for the period of 2000–2015.

Prior to computing a commodity price shock variable, unit root tests were conducted in order to ensure that all variables were stationary. This was performed in light of the concern raised by Kinda et al. (2016) that the commodity price measure above does not account for the potential trend related to price changes, making the commodity price measure nonstationary. A Phillips–Perron unit root test (Phillips 1987; Phillips and Perron 1988) with a time trend and lag of 5 was computed for all the relevant variables. The results reported in Table A4 show that all variables, including the commodity price shock (CPS) variable, contained no unit roots at level and were, therefore, stationary[10]. Two additional CPS variables were computed by splitting the original shock into positive and negative commodity shocks during estimation. This allowed the study to test for symmetry between positive and negative CPSs[11].

5. Empirical Results and Discussion

5.1. Descriptive and Correlation Analysis

Tables A5 and A6 provide the summary statistics and correlation analysis of the variables employed in the study, respectively. The mean for the dependent variable, NPL (credit risk), was 9.187; this was much higher than those obtained in other developing countries. According to Dietrich and Wanzenried (2014), the mean NPLs for low, middle, and high income economies were 1.990, 1.970, and 0.730, respectively. This high NPL level emphasizes the risk and vulnerability faced by banks in commodity-exporting African economies. There are advanced economies with elevated levels of NPLs, although the average is still below the 9.187 established in this study. In Europe, for example, the average rate of NPLs in 2016 was 5.1% (Magnus et al. 2017), which is also much higher than the 0.73 average established by Dietrich and Wanzenried (2014).

The mean for the capital adequacy ratio (NPL provisioning) was substantially high at 61.558%, indicating that African banks are safe and highly likely to meet their financial obligations[12]. The mean value for profitability (return on assets) is 1.958; it is almost in line but slightly lower than what was established for Middle East and North Africa (MENA) and sub-Saharan African banks, where values have been reported at 2.250 and 2.35, respectively (Flamini et al. 2009; Poghosyan and Hesse 2009). The mean liquidity ratio was substantially high at 29.838 in comparison to the average growth in deposits for low, middle, and high income countries of 21.630, 14.290, and 7.621, respectively (Dietrich and Wanzenried 2014). This high liquidity ratio implied that African banks are in a position to sufficiently cover current debt obligations without needing to raise funds in the capital markets.

The correlation matrix (Table A6) indicates that the CPS variable was positively correlated to NPL (0.128). A positive relationship was also observed between the CPS variable and the other banking sector variables in the study (capital adequacy (0.009), profitability (0.081), and liquidity (0.093)), emphasising the possible impact of commodity price dynamics on the banking sector, as established by Kinda et al. (2016). Another important negative correlation was that of the CPS and domestic credit extension (−0.115); this correlation is in line with findings from Agarwal et al. (2017).

Unemployment had the strongest negative relationship with NPL; this was expected, since loss of revenue weighs on the ability to service debt and vice versa. NPL was also highly negatively related to government revenue (−0.246) and domestic credit (−0.196). The correlation between NPL and real economic growth was also negative and significant (−0.014), but not as strong.

5.2. Results

The baseline model presented in Table 1 shows that the CPS coefficient increased credit risk (non-performing loans). This finding was the same across all three models, but the pooled OLS and SGMM models had weaknesses. The pooled OLS model was biased because it failed to account for the unique differences between countries, which could impact the dependent variable. On the other hand, the SGMM model was inconsistent because it failed the Sargan test. This indicated that the pooled OLS and the SGMM models were not appropriate models for this study; going forward, only the FE results are presented and discussed.

Table 1. Baseline results: the impact of commodity price shocks on NPLs.

Dependent Variable: NPL (Credit Risk)					
	POLS	**SGMM**	**FE**	**Positive**	**Negative**
NPL (lagged)		0.603 ***			
		(0.004)			
CPS	0.325 **	0.525 ***	0.381 ***	0.926 ***	0.218
	(0.127)	(0.097)	(0.094)	(0.279)	(0.261)
Capital adequacy	−0.009 ***	0.006 ***	0.026 ***	0.027 ***	0.025 ***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Profitability	−3.080 ***	−0.364 ***	−0.835 ***	−1.149 ***	−0.746 ***
	(0.042)	(0.042)	(0.044)	(0.085)	(0.090)
Liquidity	−0.081 ***	0.069 ***	0.108 ***	0.122 ***	0.105 ***
	(0.004)	(0.005)	(0.005)	(0.008)	(0.007)
Economic growth	−0.195 ***	−0.230 ***	−0.068 ***	−0.157 ***	0.010
	(0.013)	(0.011)	(0.008)	(0.016)	(0.013)
Inflation	0.461 ***	0.076 ***	−0.009	−0.023 *	0.001
	(0.008)	(0.006)	(0.008)	(0.013)	(0.015)
Unemployment	−0.453 ***	−0.156 ***	0.016	0.054 ***	−0.009
	(0.007)	(0.009)	(0.012)	(0.017)	(0.020)
Gov. revenue	0.075 ***	0.074 ***	−0.080 ***	−0.123 ***	−0.034
	(0.008)	(0.010)	(0.011)	(0.022)	(0.024)
Lending rate	−0.052 ***	0.040 ***	−0.015	−0.006	−0.078 ***
	(0.013)	(0.015)	(0.020)	(0.028)	(0.030)
M2 and reserves	−0.205 ***	−0.056 ***	−0.695 ***	−0.684 ***	−0.679 ***
	(0.016)	(0.018)	(0.014)	(0.022)	(0.023)
Exchange rate	−0.173 ***	0.048 ***	−0.023 ***	−0.016 ***	−0.029 ***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)
National savings	−0.176 ***	−0.085 ***	0.198 ***	0.242 ***	0.204 ***
	(0.005)	(0.007)	(0.013)	(0.018)	(0.018)
Constant	22.765 ***	4.486 ***	6.843 ***	7.146 ***	6.300 ***
	(0.419)	(0.471)	(0.498)	(0.735)	(0.693)
Observations	41,421	41,421	41,421	21,936	19,485
R-squared	0.336		0.143	0.156	0.158
Number of newid		7931	7931	6914	7001
F-statistics	5022.600		1729.77		
	(0.000)		(0.000)		
Wald chi-squared		56,726.550			
		(0.000)			
Sargan		29,804.040			
		(0.000)			

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Discussing the results in more detail shows that a one-unit change in the CPS yielded a 0.381% increase in credit risk (Column 4, Table 1). The CPS coefficient of 0.381% was positive and strongly significant at a 1% level of significance. These findings are in line with similar studies (Kinda et al. 2016). The study, therefore, concluded that CPS increases bank credit risk and, thus, poses a risk to the stability of African commodity-exporting economies' banking sectors. This finding adds to the current limited literature on the relationship between CPSs and banking sector stability. Most importantly, it emphasizes that CPSs can yield both macroeconomic and banking sector instability risks.

Briefly focussing on the other banking variables, the coefficient for profitability behaved as expected and was strongly significant at a 1% level of significance. The capital adequacy and the liquidity coefficients did not yield the expected signs, but they were also strongly significant at a 1% level of significance. Basel 3 requirements maintain that rising capital adequacy requirements should act as a safety net for the banking sector and uphold financial stability (Bank for International Settlements 2010), hence the prior statement that it would decrease credit risk. Oduor et al. (2017) established that higher capital adequacy ratios do not necessarily make African banks safer. Similarly, higher liquidity may also not necessarily mean safer banking systems in the case of African countries.

With the macroeconomic variables, real economic growth behaved as expected and was strongly significant at a 1% level of significance. The unemployment and inflation coefficients behaved as expected but were insignificant at all levels. All other macroeconomic variables yielded the expected signs and were significant.

While the CPS variable (Column 4, Table 1 in the previous page) provided valuable information about the impact of unexpected CPSs on banking sector stability, it did not provide any information on whether the impact of a positive CPS on banking sector stability differed from that of a negative CPS. The baseline model was augmented by positive and negative CPS variables in the next estimation.

The estimation results reported in Columns 5 and 6 in Table 1 suggested that positive CPSs in African commodity-exporting economies have a bigger impact on credit risk than negative CPSs. The results indicate that a unit increase in the CPS variable increased credit risk by 0.926% with a 1% level of significance. Even though the negative CPS also increased credit risk, the effect of the coefficient was not significant. These results are not in line with similar studies on the impact of CPSs on banking sector stability (Kinda et al. 2016). These interesting findings are partly explained by the results of Addison et al. (2016), who found, using a similar CPS measure, that positive and negative agricultural CPSs in sub-Saharan African countries did not necessarily respond differently from responses in economic growth[13]. These findings emphasize the importance of disaggregating shocks and isolating the African region because African banking sectors do not seem to respond to positive and negative CPSs in the same manner as those of other developing countries.

5.3. Sensitivity Analysis—Commodity Sub-Categories

This section examines how the banking sector was impacted by the different commodity group shocks, comparing its findings to those reported in the baseline models. The results for the disaggregated commodities are reported in Tables A7–A10.

The estimation results reported in Table A7 suggested that agricultural price shocks increased credit risk and, thus, pose a risk to banking sector stability. The agricultural price shock indicated that a one-unit increase in the agricultural price shock resulted in a 0.394% increase in credit risk; the coefficient was significant at a 1% level of significance. When disaggregated, the results yielded positive coefficients for both the positive and negative agricultural price shocks, but the effect of the coefficients were not significant. The result of no asymmetry between a positive and negative agricultural price shock in African economies was again reiterated in line with the baseline model and Addison et al. (2016).

Table A8 indicates that the mineral and fuel price shock had a positive but insignificant (0.404%) effect on bank credit risk. Further, the disaggregated result (Columns 2 and 3 of Table A8) yielded negative (−0.122%) and positive (1.029%) coefficients for the positive and negative price shocks, as expected, but with no significant[14] impact on credit risk. Even though insignificant, these results behaved as expected and were in line with previous studies that had focused specifically on mineral- and fuel- exporting countries (Poghosyan and Hesse 2009; Alodayni 2016; Miyajima 2016; Al-Khazali and Mirzaei 2017). Al-Khazali and Mirzaei (2017) also finds evidence of asymmetric mineral and fuel price shocks. These findings imply that mineral and fuel commodities are one of the main (or only) commodities where the findings for Africa are exactly in line with those of other developing countries.

The estimation results in Table A9 suggested that metal price shocks significantly increased bank credit risk, with a unit increase in the metal price shock resulting in a 0.324% increase in credit risk at a 10% level of significance. Results for the disaggregated shocks indicated that, with a one-unit increase for the positive, metal price shock increased credit risk by 1.109% at a 5% level of significance. While a negative metal price shock yielded the expected positive sign, the effect was insignificant at all levels. The results behaved as the agricultural results, showing no asymmetry between positive and negative metal price shocks. This implies that metal price fluctuations, in general, could pose a threat to banking sector stability in African countries.

Table A10 presents the results for the chemicals commodity group. The chemicals price shock had a positive but insignificant impact on credit risk (0.375%). The positive chemical price shock was also positive but highly significant with a coefficient of 2.332%. None of the African countries included in the study export chemicals[15], so it was not surprising that a positive chemical price shock resulted in a large increase in bank credit risk. Conversely, a negative chemical price shock yielded a negative coefficient (−0.449%) with no significant effect on credit risk. These results imply that, even though African economies are not exporters of chemicals, their banking systems are still vulnerable to rising chemical price shocks, probably as a result of the exposure of the firms to whom they lend.

5.4. Do Commodity Price Shocks Impact Domestic Lending?

The empirical estimations so far have shown that CPSs increase bank credit risk and, as such, pose a threat to the stability of the banking sector. While instability in the banking sector has been shown to trickle down into the real economy (Agarwal et al. 2017), this section examines whether CPSs have a direct impact on domestic credit extension in commodity-exporting economies.

The results in Table 2 (below) show that the CPS yielded a negative coefficient of −0.053% (as expected) but that it had no significant effect on bank credit extension. When disaggregated, the results revealed that a positive shock increased domestic credit extension (as one would expect) by 0.667% and was significant at a 1% level of significance. Further, the negative shock indicated that commodity price busts substantially decreased domestic credit extension (−0.910%); this result was also established to be significant at a 1% level of significance. These results are in line with Greenwald et al. (1984) and Stiglitz (2016), who said that macroeconomic conditions that have implications for bank balance sheets or that increase risk perceptions usually lead to a contraction in the supply of funds by banks. The findings are also supported by the findings of Agarwal et al. (2017).

In addition to the aggregated findings, Tables A11–A14 show that the overall agricultural, mineral, fuel, and metal price shocks had no significant effect on credit extension in commodity-exporting African economies. However, the overall chemical price shock was found to statistically and significantly decrease credit extension by 0.377% in African countries. The exposure of banks in the sector could be direct or indirect (through firms that are exposed to the sector to which banks lend). When disaggregated, positive agricultural and chemical price shocks, again, had no significant effect on credit extension. However, the mineral, fuel, and metal positive shocks were found to statistically and significantly increase credit extension. Finally, negative price shocks in the mineral, fuel, chemical, and metal commodity groups seemed to have large negative impacts on bank lending in African countries. It is important to outline that, while all coefficients for the agricultural group were insignificant, the results did indeed show the true reality of the agricultural sector in African countries. The agricultural sector has constantly struggled and continues to struggle with accessing funding from the banking sector (Varangis 2018). Therefore, it is not entirely surprising that agricultural shocks had no significant effect on bank lending. The statistically significant findings are in line with Greenwald et al. (1984) and Stiglitz (2016), who said that macroeconomic conditions that have implications for bank balance sheets or that increase risk perceptions usually lead to a contraction in the supply of funds by banks. These findings are further supported by the findings of Agarwal et al. (2017). As previously observed, the African countries included in this sample have extremely high capital adequacy ratios. High capital adequacy ratios have a negative impact on bank lending, since they limit the amount available for lending. This, combined with the fact that CPSs decrease lending, could, therefore, worsen lending conditions and stifle economic growth and development. Overall, the results revealed that certain CPSs not only weaken banking sector stability through credit risk but could also have a direct impact on bank credit extension.

Table 2. The impact of commodity price shocks on credit extension.

Dependent Variable: Domestic Credit Extension	Overall	Positive	Negative
Commodity price shock	−0.053	0.667 ***	−0.910 ***
	(0.074)	(0.247)	(0.276)
Real economic growth	0.304 ***	0.288 ***	0.346 ***
	(0.010)	(0.013)	(0.016)
Unemployment	−0.660 ***	−0.674 ***	−0.690 ***
	(0.021)	(0.026)	(0.026)
Savings	−0.874 ***	−0.875 ***	−0.890 ***
	(0.021)	(0.024)	(0.026)
Lending rate	−0.101 ***	−0.086 ***	−0.100 ***
	(0.014)	(0.017)	(0.017)
Constant	67.718 ***	67.684 ***	68.050 ***
	(0.518)	(0.632)	(0.657)
Observations	65,053	34,442	30,611
R-squared	0.173	0.173	0.179
Number of newid	9470	8293	8348

Note: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6. Conclusions

Considering the volatility of commodity prices and African economies' dependence on commodities, this study investigated the impact of CPSs on the banking system stability of African commodity-exporting economies. The study employed a FE model on a sample of 18 African commodity-exporting economies. The findings revealed that CPSs are associated with a rise in bank credit risk (NPL) and, thus, pose a risk to the banking sector stability of African commodity-exporting countries. An important finding from this study was that positive and negative CPSs do not necessarily vary in their impact on banking sector stability. This finding is not in line with previous studies (Kinda et al. 2016). These results are supported by Addison et al. (2016), who established that positive and negative agricultural price shocks in African countries do not necessarily yield asymmetric results[16].

When disaggregated, the agricultural and metal price shocks behaved as in the baseline model, with the shocks increasing credit risk and, thus, posing a threat to banking sector stability. These two commodity groups indicated no asymmetry as both positive and negative shocks yielded positive signs. The positive metal price shock was the only statistically significant coefficient. The positive and negative mineral and fuels shock yielded the desired effects, but none was statistically significant. The mineral and fuel sector was the only commodity group that seemed to behave in line with other developing countries. In contrast, a positive chemical price shock significantly increased bank credit risk, which can possibly be explained by the fact that African economies import more chemicals than they export. The negative chemical price yielded the expected sign but was statistically significant. The results for the mineral, fuel, and chemical commodity groups indicated asymmetry when the CPS was disaggregated.

Following the estimation of the impact of CPSs on bank lending, the findings indicated that CPSs decrease bank lending. When disaggregated, the results revealed that positive CPSs insignificantly increased bank lending but that a negative CPS substantially and significantly decreased bank lending. These results suggested that, while a positive CPS boosts bank lending, the boost is not to the same magnitude that a negative CPS decreases bank lending. Further, negative price shocks in the mineral, fuel, chemical, and metal commodity groups seemed to have large negative impacts on bank lending in African countries. Therefore, the study deduced that, even though CPSs weaken banking sector stability through credit risk, they could also have a direct impact on bank lending as bank perceptions of macroeconomic risks rise. The results of this study cannot be generalized for all developing countries given that the banking system and financial sector of the African region differs from other regions of the world.

The main policy implication of this study is that it highlighted that commodity price shocks can impact the banking sector of African commodity-dependent countries. This finding implies that African countries need to adopt and implement policies that protect the banking sector from CPSs. The study makes the following recommendations: First, considering the finding that commodity price shocks can impact the banking sector, as well as credit extension to the private sector, African central banks need to strengthen the macroprudential regulation and oversight of the banking sector in order to ensure that it remains resilient to CPSs. Further, their policies should help mitigate systemic risk so that the vulnerabilities faced by one sector do not spill over to other sectors in the economy. Second, the study also found that both positive and negative shocks weigh on banking sector stability. This finding highlights the need for African economies to extensively diversify their exports and economic activities. A more diversified economy means that countries can rely on alternative sources of revenue. This is especially important for the agricultural and metal-dependent African countries. Third, in line with the finding that mineral and fuel, as well as chemical, price shocks resulted in a substantial increase in credit risk, African economies must establish and maintain a robust sovereign wealth fund[17] that can be used to protect the economies from excess export revenue volatility.

The managerial implications of this study are: (i) Bank managers and the financial sector should put mechanisms in place such as consistently maintaining enough fiscal reserves (e.g., through the establishment of a sovereign wealth fund) because this will help reduce the detrimental impact that is usually associated with commodity price fluctuations on the banking system. (ii) Bank managers and the financial sector should partner with the government by strongly supporting the development of counter-cyclical capital buffers that will help mitigate the impact of commodity price shocks on bank balance sheets. (iii) Bank managers and stakeholders in the banking sector should closely and regularly monitor and anticipate uncertainty that may likely occur in the return process of agricultural projects, since, by nature, agricultural projects supported by loans are sensitive to many risk factors (e.g., price of inputs, demand, weather conditions, and uncertainty of spot price of produce). (iv) Stakeholders in the banking sector should adopt macroprudential policies, since they act as an important factor for the stability of the financial sector and given that they are also gaining attention internationally as a useful tool to address system-wide risks in the banking sector. (v) Bank managers and stakeholders should revisit prudent guidelines to stem the credit risks associated with the systemic risks of oil price volatility and should also consider establishing early warning and response mechanisms for commodity price shocks in order to operate with better performance.

Provided that this study focused on 18 African commodity-exporting economies, it would be beneficial for future research to probe the CPS and banking sector stability relationship for a single commodity-exporting country. The study used aggregated banking data; it would be extremely interesting to analyze this relationship at a bank-specific level for African economies, as it would provide more granular information on the banks that pose the greatest risk to banking sector stability. In addition, with the popularity of cross-border bank expansions in Africa, research on whether banking sector instability in a host country (and resulting CPSs) exacerbates banking sector instability in the home country would also be of interest. Finally, the NPL data employed in the study were aggregated; it would be extremely useful to find granular data that separates credit risk by government, corporate, and household sectors.

The biggest difficulty with this study was data collection. Data for African economies are quite difficult to collect, and this made it impossible to include a larger sample of African countries. Additionally, the dataset was unbalanced, but the econometric method employed was suitable for an unbalanced dataset. Another limitation of this study was that it could not extend the period to cover the COVID-19 pandemic period due to data problems for the variables used. Therefore, future studies should take into account the pandemic period for the purpose of obtaining a better understanding in terms of the impact of commodity price shocks on banking system stability in developing countries. Future studies should also investigate by forecasting the commodity price shocks and the possible impact they will have on the banking system stability of developing countries.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. List of countries included in the sample.

1.	Botswana	2.	Mozambique
3.	Egypt	4.	Namibia
5.	Gabon	6.	Nigeria
7.	Ghana	8.	Rwanda
9.	Kenya	10.	Senegal
11.	Lesotho	12.	Sierra Leone
13.	Mauritius	14.	South Africa
15.	Morocco	16.	Swaziland
17.	Tunisia	18.	Uganda

Table A2. Commodity groups included in the sample.

1.	Aluminum	2.	Inorganic Chemicals
3.	Cocoa	4.	Coffee, Tea, and Spices
5.	Copper	6.	Cotton
7.	Dairy	8.	Fish
9.	Fruit	10.	Iron
11.	Lead	12.	Livestock
13.	Trees	14.	Meat
15.	Minerals and Fuels	16.	Nickel

Table A2. *Cont.*

17.	Ores	18.	Organic Metals
19.	Precious Metals	20.	Animal Products
21.	Hides	22.	Silk
23.	Salts	24.	Sugar
25.	Tin	26.	Tobacco
27.	Vegetables	28.	Wheat
29.	Wool	30.	Zinc
31.	Organic Chemicals		

Table A3. Data description and sources.

Variables	Description	Sources	Expected Impact
Dependent variable			
Non-performing loan	The value of NPLs to total value of loans (annual %)	WB	+/-
Financial stability indicators (FSIs)			
Capital adequacy		FRED/WB	-
Profitability	Net income to yearly averaged total assets (annual %)	FRED/WB	-
Liquidity	Value of liquid assets to short-term funding plus total deposits	FRED/WB	-
Macroeconomic/control variables			
Commodities	Annual trade value of exported commodities	UN Comtrade	+
Real economic growth	Annual % growth rate at constant prices	WB	-
Inflation	Annual % consumer prices	WB	-
Unemployment.	Unemployment as a % of total labor force	WB	+
Credit extension	Credit to private sector by bank (% of GDP)	WB	+
Government revenue	All taxed, excluding grants (% of GDP)	WB	-
Lending rate	Lending interest rate %	WB	-
M2 and reserves	Broad money to international reserves	FRED	-
Exchange rate	Annual percentage change exchange rate	Penn World Table 9.0	+
Savings	GDP minus final consumption expenditure (% of GDP)	WB	-
Commodity price shock determinant			
Commodity price shock (CPS)	Real oil price change (Farzanegan and Markwardt 2009; Mork 1989)	UN Comtrade	+

Source: Author collection.

Table A4. Phillip-Perron unit root test.

Variables	Level
Non-performing loans	4243.23 (0.00) ***
Capital adequacy	4416.50 (0.00) ***
Profitability	7623.87 (0.00) ***
Liquidity	4238.25 (0.00) ***
Real economic growth	10,300.00 (0.00) ***
Inflation	5084.31 (0.00) ***
Unemployment	2581.38 (0.00) ***
Government revenue	4030.54 (0.00) ***
Lending rate	1094.76 (0.00) ***
Domestic credit extension	3786.62 (0.00) ***
M2 and reserves	1980.33 (0.00) ***
Exchange rate	4219.53 (0.00) ***
Savings	2379.46 (0.00) ***
Commodity price shock	16,200.00 (0.00) ***

Source: Author computations. H_0: All panels contain unit roots; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5. Descriptive statistics.

Variable	Obs	Mean	Std Dev	Min	Max
Non-performing loans	41,421	9.187	8.153	1.000	74.100
Capital adequacy	41,421	61.558	24.520	1.800	188.100
Profitability	41,421	1.958	1.378	−0.630	9.910
Liquidity	40,415	29.838	12.384	6.520	90.680
Real economic growth	41,421	4.474	2.685	−20.491	26.269
Inflation	41,386	6.458	4.601	−3.286	32.905
Unemployment	41,421	15.307	8.120	0.744	37.600
Government revenue	39,674	24.694	7.737	4.977	63.512
Lending rate	39,276	13.520	4.446	4.460	26.708
Domestic credit	41,421	43.089	23.494	1.944	106.260
M2 and external reserves	41,235	4.493	3.383	0.227	55.924
Exchange rate	40,754	4.458	13.438	−28.233	104.363
Savings	41,412	16.195	9.739	−37.008	60.490
Commodity price shock	41,421	0.160	0.466	−2.290	2.858

Source: Author computations.

Table A6. Correlation matrix.

	Non-Performing Loan	Capital Adequacy	Profitability	Liquidity	Real GDP	Unemployment	Gov. Revenue	Domestic Credit	Commodity Price Shock
NPL	1.000								
Capital adequacy	−0.104 ***	1.000							
Profitability	−0.241 ***	0.196 ***	1.000						
Liquidity	0.074 ***	−0.010 ***	0.007 **	1.000					
Real GDP	−0.014 ***	0.183 ***	0.289 ***	0.126 ***	1.000				
Unemployment	−0.426 ***	−0.019 ***	−0.050 ***	−0.232 ***	−0.234 ***	1.000			
Gov. revenue	−0.246 ***	0.142 ***	−0.190 ***	−0.267 ***	−0.157 ***	0.655 ***	1.000		
Domestic credit	−0.196 ***	−0.324 ***	−0.479 ***	−0.158 ***	−0.286 ***	0.349 ***	0.414 ***	1.000	
Commodity price shock	0.128 ***	0.009 **	0.081 ***	0.093 ***	0.005	−0.040 ***	−0.105 ***	−0.115 ***	1.000

Source: Author computations. *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.10$.

Table A7. Agricultural commodity price shock and the banking sector.

Dependent Variable: Credit Risk			
	Overall	**Positive**	**Negative**
Commodity price shock	0.394 ***	0.451	0.199
	(0.152)	(0.459)	(0.402)
Capital adequacy	0.019 ***	0.022 ***	0.012 **
	(0.003)	(0.005)	(0.005)
Profitability	−0.752 ***	−1.364 ***	−0.343 ***
	(0.064)	(0.132)	(0.125)
Liquidity	0.083 ***	0.088 ***	0.086 ***
	(0.006)	(0.009)	(0.009)
Real economic growth	−0.075 ***	−0.129 ***	−0.031 *
	(0.010)	(0.021)	(0.017)
Inflation	−0.039 ***	−0.047 **	−0.052 **
	(0.013)	(0.021)	(0.022)

Table A7. *Cont.*

Dependent Variable: Credit Risk	**Overall**	**Positive**	**Negative**
Unemployment	−0.039 **	0.005	−0.068 ***
	(0.017)	(0.025)	(0.025)
Government revenue	−0.110 ***	−0.183 ***	−0.047
	(0.015)	(0.031)	(0.033)
Lending rate	0.010	0.113 **	−0.151 ***
	(0.031)	(0.044)	(0.044)
M2 and reserves	−0.779 ***	−0.777 ***	−0.762 ***
	(0.019)	(0.032)	(0.031)
Exchange rate	0.004	0.001	0.012
	(0.005)	(0.007)	(0.009)
Savings	0.175 ***	0.183 ***	0.212 ***
	(0.018)	(0.027)	(0.022)
Constant	9.345 ***	10.163 ***	9.204 ***
	(0.694)	(0.974)	(1.001)
Observations	16,545	8898	7647
R-squared	0.157	0.168	0.185
Number of newid	2884	2566	2607

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **Source**: Author computations.

Table A8. Mineral and fuel commodity price shock and the banking sector.

Dependent Variable: Credit Risk	**Overall**	**Positive**	**Negative**
Commodity price shock	0.404	−0.122	1.029
	(0.282)	(0.774)	(0.750)
Capital adequacy	0.012 **	0.004	0.025 **
	(0.006)	(0.009)	(0.010)
Profitability	−0.734 ***	−0.187	−1.440 ***
	(0.007)	(0.010)	(0.008)
Liquidity	0.113 ***	0.132 ***	0.117 ***
	(0.015)	(0.025)	(0.020)
Real economic growth	−0.055 **	−0.212 ***	0.023
	(0.022)	(0.051)	(0.036)
Inflation	−0.065 **	−0.082 *	−0.081 *
	(0.028)	(0.042)	(0.047)
Unemployment	−0.002	−0.042	0.049
	(0.033)	(0.046)	(0.051)
Government revenue	−0.051 **	−0.059	−0.002
	(0.026)	(0.063)	(0.053)
Lending rate	−0.008	−0.033	−0.013
	(0.062)	(0.079)	(0.093)
M2 and reserves	−0.665 ***	−0.716 ***	−0.558 ***
	(0.037)	(0.067)	(0.057)
Exchange rate	−0.016	0.010	−0.035 *
	(0.010)	(0.013)	(0.020)
Savings	0.189 ***	0.206 ***	0.230 ***
	(0.036)	(0.048)	(0.037)
Constant	7.663 ***	8.396 ***	5.365 ***
	(1.497)	(2.499)	(1.915)
Observations	4235	2250	1985
R-squared	0.163	0.147	0.215
Number of newid	796	708	694

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **Source**: Author computations.

Table A9. Metal commodity price shock and the banking sector.

Dependent Variable: Credit Risk	**Overall**	**Positive**	**Negative**
Commodity price shock	0.324 *	1.109 **	0.372
	(0.174)	(0.455)	(0.478)
Capital adequacy	0.025 ***	0.034 ***	0.012 *
	(0.004)	(0.005)	(0.007)
Profitability	−0.742 ***	−1.484 ***	−0.375 **
	(0.093)	(0.163)	(0.188)
Liquidity	0.087 ***	0.120 ***	0.063 ***
	(0.011)	(0.015)	(0.015)
Real economic growth	−0.021	−0.048 *	0.052 **
	(0.013)	(0.028)	(0.023)
Inflation	0.004	−0.011	−0.011
	(0.016)	(0.028)	(0.030)
Unemployment	−0.012	0.099 ***	−0.104 **
	(0.023)	(0.031)	(0.041)
Government revenue	−0.039 **	−0.100 **	0.047
	(0.020)	(0.041)	(0.047)
Lending rate	0.013	−0.032	−0.001
	(0.040)	(0.053)	(0.061)
M2 and reserves	−0.681 ***	−0.657 ***	−0.654 ***
	(0.029)	(0.043)	(0.047)
Exchange rate	−0.031 ***	−0.041 ***	−0.023 *
	(0.006)	(0.009)	(0.012)
Savings	0.134 ***	0.227 ***	0.080 **
	(0.025)	(0.033)	(0.038)
Constant	6.248 ***	5.462 ***	6.912 ***
	(0.937)	(1.378)	(1.365)
Observations	10,847	5608	5239
R-squared	0.114	0.162	0.103
Number of newid	2154	1862	1888

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **Source**: Author computations.

Table A10. Chemical commodity price shock and the banking sector.

Dependent Variable: Credit Risk	**Overall**	**Positive**	**Negative**
Commodity price shock	0.375	2.332 ***	−0.449
	(0.232)	(0.746)	(0.674)
Capital adequacy	0.063 ***	0.053 ***	0.085 ***
	(0.004)	(0.008)	(0.009)
Profitability	−0.431 ***	0.065	−1.191 ***
	(0.155)	(0.249)	(0.277)
Liquidity	0.324 ***	0.352 ***	0.300 ***
	(0.028)	(0.040)	(0.037)
Real economic growth	−0.223 ***	−0.404 ***	−0.070
	(0.033)	(0.064)	(0.064)
Inflation	0.033 **	0.003	0.105 ***
	(0.016)	(0.028)	(0.041)
Unemployment	0.276 ***	0.256 ***	0.363 ***
	(0.037)	(0.051)	(0.076)
Government revenue	−0.089 *	−0.013	−0.219 **
	(0.048)	(0.073)	(0.102)
Lending rate	−0.169 ***	−0.250 ***	−0.136 **
	(0.047)	(0.066)	(0.066)
M2 and reserves	−0.456 ***	−0.316 ***	−0.602 ***
	(0.052)	(0.090)	(0.086)

Table A10. *Cont.*

Dependent Variable: Credit Risk	Overall	Positive	Negative
Exchange rate	−0.059 ***	−0.023 **	−0.093 ***
	(0.007)	(0.011)	(0.013)
Savings	0.487 ***	0.593 ***	0.495 ***
	(0.049)	(0.062)	(0.084)
Constant	−7.477 ***	−10.660 ***	−5.887 **
	(2.126)	(3.044)	(2.976)
Observations	8028	4284	3744
R-squared	0.245	0.244	0.304
Number of newid	1705	1441	1476

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **Source**: Author computations.

Table A11. The impact of agricultural price shocks on credit extension.

Dependent Variable: Domestic Credit Extension	Overall	Positive	Negative
Commodity price shock	0.074	0.019	−0.562
	(0.117)	(0.390)	(0.440)
Real economic growth	0.233 ***	0.219 ***	0.258 ***
	(0.015)	(0.020)	(0.023)
Unemployment	−0.610 ***	−0.645 ***	−0.611 ***
	(0.033)	(0.041)	(0.041)
Savings	−0.976 ***	−0.934 ***	−1.042 ***
	(0.034)	(0.040)	(0.040)
Lending rate	−0.034	−0.019	−0.023
	(0.021)	(0.026)	(0.025)
Constant	63.688 ***	63.701 ***	63.965 ***
	(0.791)	(0.990)	(0.963)
Observations	25,381	13,553	11,828
R-squared	0.168	0.158	0.184
Number of newid	3442	3083	3103

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **Source**: Author computations.

Table A12. The impact of mineral and fuel price shocks on credit extension.

Dependent Variable: Domestic Credit Extension	Overall	Positive	Negative
Commodity price shock	0.094	2.145 ***	−2.176 **
	(0.226)	(0.751)	(0.917)
Real economic growth	0.324 ***	0.308 ***	0.360 ***
	(0.027)	(0.038)	(0.040)
Unemployment	−0.539 ***	−0.540 ***	−0.563 ***
	(0.057)	(0.066)	(0.072)
Savings	−0.717 ***	−0.667 ***	−0.834 ***
	(0.068)	(0.078)	(0.086)
Lending rate	0.026	−0.005	0.068
	(0.039)	(0.043)	(0.047)
Constant	58.570 ***	58.569 ***	58.823 ***
	(1.524)	(1.740)	(1.971)
Observations	6443	3430	3013
R-squared	0.118	0.114	0.142
Number of newid	954	853	832

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **Source**: Author computations.

Table A13. The impact of metal price shocks on credit extension.

Dependent Variable: Domestic Credit Extension	**Overall**	**Positive**	**Negative**
Commodity price shock	−0.167	1.396 ***	−0.849 *
	(0.137)	(0.458)	(0.503)
Real economic growth	0.326 ***	0.326 ***	0.356 ***
	(0.019)	(0.026)	(0.030)
Unemployment	−0.533 ***	−0.504 ***	−0.589 ***
	(0.031)	(0.038)	(0.041)
Savings	−0.894 ***	−0.940 ***	−0.850 ***
	(0.040)	(0.043)	(0.052)
Lending rate	−0.157 ***	−0.118 ***	−0.182 ***
	(0.025)	(0.028)	(0.032)
Constant	66.725 ***	65.841 ***	67.323 ***
	(0.887)	(1.034)	(1.152)
Observations	17,063	8930	8133
R-squared	0.194	0.199	0.189
Number of newid	2540	2201	2240

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **Source**: Author computations.

Table A14. The impact of chemical price shocks on credit extension.

Dependent Variable: Domestic Credit Extension	**Overall**	**Positive**	**Negative**
Commodity price shock	−0.377 **	−0.063	−1.205 *
	(0.185)	(0.612)	(0.636)
Real economic growth	0.348 ***	0.309 ***	0.406 ***
	(0.027)	(0.037)	(0.045)
Unemployment	−1.192 ***	−1.295 ***	−1.251 ***
	(0.072)	(0.097)	(0.094)
Savings	−0.662 ***	−0.693 ***	−0.611 ***
	(0.038)	(0.043)	(0.048)
Lending rate	−0.365 ***	−0.390 ***	−0.373 ***
	(0.049)	(0.060)	(0.062)
Constant	87.218 ***	89.746 ***	87.698 ***
	(1.791)	(2.327)	(2.395)
Observations	13,453	7162	6291
R-squared	0.225	0.248	0.217
Number of newid	2084	1767	1782

Robust standard errors in parentheses; *** $p < 0.01$, ** p < 0.05, * $p < 0.1$. **Source**: Author computations.

Notes

1. This increase represents the magnitude of the shock. This is a shock that does not distinguish between a negative or positive shock.
2. Credit extension to the private sector and bank lending are used interchangeably.
3. A shock in one institution or economy that spreads and impacts other institutions or economies.
4. Competitiveness of companies that depend on government contracts is compromised.
5. Run on a bank occurs when a large number of depositors, fearing that their bank will be unable to repay their deposits in full and on time, simultaneously try to withdraw their funds immediately.
6. Capital adequacy, asset quality, earnings, profitability, liquidity, and sensitivity to market risk (IMF 2006).
7. Breusch-Pagan Lagrangian multiplier and Hausman tests further motivated the use of the panel fixed effects model for the study.
8. Sargan's test of over-identified instruments tests the overall validity of the instruments used in the estimation process.
9. Represents the number of days in a year.
10. Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC) and Hannan and Quinn's Information Criterion (HQIC) tests were computed per country to determine the most appropriate lag length.
11. Therefore, the study has three various shocks: a CPS (1), a positive CPS, and a negative CPS.
12. Basel 3 regulations require banks to maintain a minimum capital adequacy ratio of only 8% (Bank for International Settlements 2010).

13 The study is not exactly related to banking sector, but the fact that the measure used obtained similar results is important for this study. Further, agriculture makes up a significantly large portion of the dataset.
14 The minerals and fuels commodity group had the smallest sample in the study. This may have contributed to the insignificance.
15 African economies import chemicals.
16 While this study did not solely focus on the agricultural sector, it constituted the largest portion of the dataset.
17 That can be built during periods of commodity price booms.

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Money Supply and Inflation after COVID-19

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Abstract: The core personal consumption expenditure (PCE) price index, the Federal Reserve's preferred inflation gauge, rose to 5.2 percent on January 2022, which is the highest rate of increase since 40 years ago. Our estimates show that the annualized quarterly core PCE prices could reach 5.45% in the second quarter of 2022 and are as high as 8.57% in a longer time horizon unless corrected with restrictive monetary policies. Thus, the inflation shock since COVID-19 is not transitory, but it is persistent. As economists expect the Federal Reserve to tighten the money supply in March 2022, the insufficient policy responses may be attributed to a failure to incorporate a unique macroeconomic shock to unemployment during the pandemic. We propose a modified vector autoregression (VAR) model to examine structural shocks after COVID-19, and our proposed model performs well in forecasting future price levels in times of a pandemic.

Keywords: inflation; forecast; time series; vector autoregressiion; pandemic; COVID-19; unemployment rate

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1. Introduction

"We tend to use [transitory] to mean that it won't leave a permanent mark in the form of higher inflation. I think it's probably a good time to retire that word and try to explain more clearly what we mean", Federal Reserve Chairman Jerome Powell said during a congressional hearing on Tuesday, 2 December 2021.

To combat the negative economic effects of COVID-19, the Federal Reserve has used an unprecedented combination of monetary and fiscal policies. Clarida et al. (2021) provides an excellent summary of how the Federal Reserve deployed its conventional tools to support the U.S. economy in 2020 and contribute to robust economic recovery in 2021. The tools included large-scale asset purchase programs (Vissing-Jorgensen 2021), near-zero interest rates, and subsidized loan programs. On top of the expansionary monetary policies, Congress authorized various types of expansionary fiscal policies, including the $2.2 trillion Coronavirus Aid, Relief, and Economic Security (CARES) Act (Bhutta et al. 2020).

These expansionary monetary and fiscal policies led to a large increase in the supply of money. Figure 1 depicts M2 money supply (M2) in seasonally adjusted billions of dollars and its percent change (M2P) at a monthly level from 1959:01 to 2022:02. M2 since 1959 shows a slow and steady growth until 2000, growing to approximately $5 trillion in the 40-year span. Between 2000 and 2020, M2 grew from $5 trillion to $15 trillion, an increase of $10 trillion in 20 years. Due to the aforementioned expansionary policies in response to COVID-19, the level of M2 grew from approximately $15 trillion in 2020:01 to $22 trillion in 2022:02, an increase of $7 trillion in 2 years. The magnitude of the increase in M2 is quite astonishing compared to the rather slow and steady historical growth. At any month since 1959 and before 2020, the monthly percent change in M2 was within 2 percent except for 2.8 percent in 1983:01, which occurred during the oil shock crisis. Even during the Global Financial Crisis of 2007–2009, the monthly growth rate was within the 2 percent range. In contrast, the COVID-19 money supply growth rate is unprecedented. In March, April, and May 2020, the money supply grew by 3.4, 6.3, and 4.9 percent, respectively.

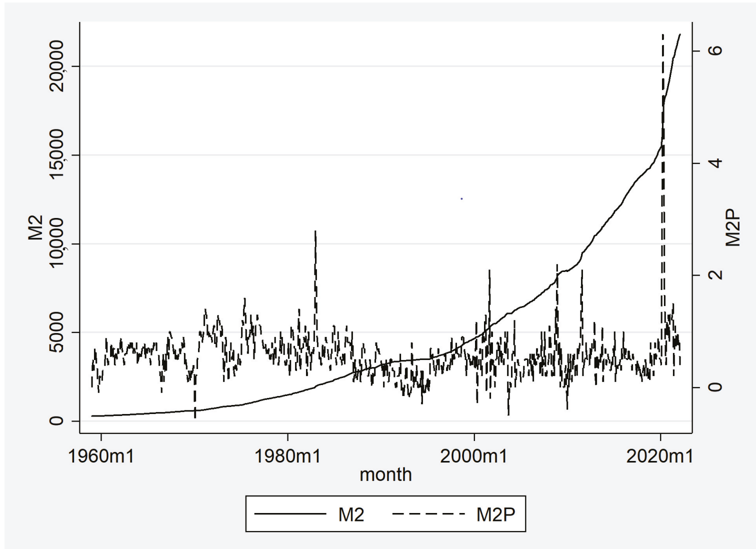

Figure 1. M2 money supply (M2, left, billions of dollars) and M2 money supply percent change (M2P, right, %), monthly, seasonally adjusted, 1959:01–2022:02, Source: Board of Governors of the U.S. Federal Reserve System.

With the increase in the money supply, the debate about its impact on inflation has reemerged. The original idea behind the relationship between the money supply and inflation stems from the quantity theory of money (Humphrey 1974). The theory states that the quantity of money in circulation primarily affected the general level of prices. Brunner and Meltzer (1972); Brunner et al. (1980); Cagan (1989); Friedman (1989); Friedman and Schwartz (2008), and other monetarists show that a sudden increase in the money supply resulted in a proportional increase in inflation, and hence, the government should curtail the money supply to control the price level. In contrast, Ball et al. (1988); Cogley and Sbordone (2008); Del Negro et al. (2015); Galí (2015), and other Keynesian economists have challenged the quantity theory of money. The main argument is that an increase in the money supply has led to a decrease in the velocity of money and a rise in real income, which would stimulate aggregate demand and the economy would achieve full employment. For instance, Mishkin (2009) contends that the expansionary monetary policy was effective in reducing adverse effects from financial disruptions and managing an upward shift in inflation risks during the Global Financial Crisis.

However, the price level in the U.S. has substantially been increasing since 2021 and well into 2022. At the end of 2021, Federal Reserve Chairman Jerome Powell acknowledged that the upward trend in inflation is no longer transitory, reversing from the original stance.[1] The headline U.S. inflation rate rose to 7.5 percent in January 2022, which is the highest rate of increase since 1982.[2] The core personal consumption expenditure (PCE) price index, the Federal Reserve's preferred inflation gauge, rose to 5.2 percent, also with the highest rate of increase since 1983.[3] Given that the core PCE prices have been well over their target rate of 2 percent, the Federal Reserve increased the interest rate on March 2022, which is a major shift in the U.S. monetary policy, and it will continue to raise the rate at least until the end of 2022, although there is a disagreement about the incremental of each raise.[4]

Forecasting inflation after COVID-19 has been a difficult task using a traditional econometric model given the unique macroeconomic variations during the pandemic. Vector autoregression (VAR) is one of the most popular models in macroeconomics to measure the responses of outcome variables to exogenous shocks and forecast future outcomes (e.g., Giordano et al. 2007; Gharehgozli et al. 2020). However, the COVID-19 pandemic has created challenges to the VAR model, as the U.S. economy experienced economic disruptions at an unprecedented scale. Namely, the unemployment rate in April 2020 was 14.7 percent, an increase of 10 percentage points in a single month. Lenza and Primiceri (2020) point out that this type of unprecedented irregularity in the data will contaminate the pre-pandemic fit of the VAR model.

To tackle the challenge of using a VAR model in times of a pandemic, macro-econometricians are trying to incorporate this outlier, extreme observation, or contamination of data into the model. The literature provides two major solutions. A first strand of literature applies restrictions to the estimation. For instance, Lenza and Primiceri (2020) suggest an ad hoc strategy of removing outliers for parameter estimation. Economists can re-scale the April 2020 parameter, provided that this re-scaling is common to all shocks. The solution provides a flexibility in the model because the exact timing of the volatility change is known, which makes it much simpler than a typical time-varying volatility model. Unfortunately, the proposed solution is not suitable for forecasting because it significantly undermines uncertainty. Schorfheide and Song (2021) suggest that an existing mixed-frequency VAR model can still be used with some modification without a major ad hoc change. However, the modification still includes excluding a few months of outliers, which could jeopardize the model's forecasting performance. A second strand of literature gets help from additional information. For instance, Foroni et al. (2020) use information from the Global Financial Crisis to adjust post-pandemic forecasts. Ng (2021) treats COVID-19 as a persistent health crisis with large economic consequences and "de-COVID" the data so that economic shocks within the VAR model can be identified. COVID-19 indicators, such as hospitalization, positive cases, and deaths, are used to either eliminate or include additional information for the modeling.

In line with the literature proposing alternatives to the traditional VAR approach, we propose a new model to examine the macroeconomic behaviors in times of a pandemic. Our model stems from the point of view that macroeconomic outcomes that originate with labor market dislocations differ from those in which labor markets play a less active role. Namely, domestic lockdown policies across different U.S. states in March and April 2020 served as an exogenous shock to unemployment. The domestic lockdown policies are unprecedented even in past epidemic episodes, which make the COVID-19 recession unique compared to any other historical crises. Furthermore, the so-called "Great Resignation", during which workers have voluntarily decided not to return to work until work safety and an increase in real wages are guaranteed, has increased instability in unemployment. Thus, we assume that the labor market has been substantially distorted during the pandemic due to exogenous shocks, such as the lockdown policies and the Great Resignation. Our logic is in sync with an argument made in Aastveit et al. (2017), which show that the association between GDP and unemployment has been shifted since the Global Financial Crisis in 2008.

The rest of this paper is structured as follows. Section 2 presents our VAR model and describes the data. Section 3 discusses findings from the main methodology and sensitivity analysis. Section 4 concludes the paper.

2. Model Specification

In this section, we introduce our VAR model and the identification scheme for the structural shocks and then discuss our data.

A VAR model is, in principle, a simple multivariate model in which each variable is explained by its own past values and the past values of all the other variables. In other words, it describes the evolution of a set of k variables, called endogenous variables, over time and, therefore, enables us to study the responses of each variable to substantial changes in others through the impulse response analysis, forecast error variance decomposition, historical decomposition, and the analysis of forecast scenarios (e.g., Hashimzade and Thornton 2021).

In the econometrics literature, the main stimulus for much recent work on VAR models is the paper by Sims (1980), based on the idea of using an unrestricted vector of past values of variables for forecasting. Since then, the literature has been full of studies in which a VAR is employed to study the relationship between economic indicators, and many of these studies are focused on the dynamics of the macroeconomic variables and the effects of events and interventions on these dynamics (e.g., Adeniran et al. 2016; Berisha 2020; Okoro 2014; Ronit and Divya 2014; Zuhroh et al. 2018).

One advantage of the VAR model is that we can typically treat all variables as a priori endogenous. Thereby, they account for Sims (1980)'s critique that the exogeneity assumptions for some of the variables in simultaneous equations models are ad hoc and often not backed by fully developed theories (e.g., Hashimzade and Thornton 2021). A VAR model does not assume any direction for the relationships unless restricted. Restrictions, including the exogeneity of some of the variables, may be imposed on VAR models based on statistical procedures. Structural VAR analysis, then, attempts to investigate structural economic hypotheses with the help of VAR models. While in the structural VAR, variables can have contemporaneous effects on each other, in a reduced-form structural VAR, the contemporaneous effects are considered in the error term, and while no variable has a direct contemporaneous effect on other variables, the occurrence of one structural shock can potentially lead to the occurrence of shocks in all error terms, thus creating contemporaneous movement in all endogenous variables.

There are some caveats in working with the VAR models. The estimation of autoregressive models requires that the data be fully observed. With the existence of missing values, this is not possible, rendering it impossible to estimate the model (e.g., Bashir and Wei 2018), or large samples of observations involving time series variables that cover many years are needed to estimate the VAR model; these are seldom available for regional studies (e.g., LeSage and Krivelyova 1999). VAR models are criticized because they do not shed any light on the underlying structure of the economy, as they do not aim to estimate causal relationships. Though this criticism is not important when the purpose of VAR is forecasting, it is relevant when the objective is to find causal relations among the macroeconomic variables.

We find that the structural VAR explained below is an appropriate model to address the inquiry of this study, which is not necessary to estimate the causal relationships between the variables in the model, but to employ their dynamics to forecast the future of the main variable of interest. The structural VAR enables us to follow and include the observed structural pattern of the economy (after the pandemic) and restrict the order of the shocks in the system to observe the responses of the variables.

2.1. Methodology

Nakamura and Steinsson (2018) provide a perspective on different identification strategies and approaches used to study the effect of monetary policy on macroeconomic indicators and describe their caveats. They give a critical assessment of several of the main methods, such as "matching moments"; those focused on identifying causal effects such as instrumental variables, difference-indifference analysis, regression discontinuities, randomized controlled trials; as well as vector autoregression. One important point they explain is the importance of finding an exogenous or surprise component of a monetary policy to assess the effects (and any "direct causal inference"). Romer and Romer (2004) suggest that the dispersion between realized values and the expected values of the indicators are the exogenous or unexpected component. Nakamura and Steinsson (2018) also discuss a standard VAR model regarding monetary policies and argue that an assumption must be made about whether the contemporaneous correlation between the variables is taken to reflect a causal influence. For instance, it is common to assume that the federal funds rate does not affect output and inflation contemporaneously.

VAR models are flexible multivariate time series models, which provide a rich account of the complex forms of autocorrelation and cross-correlation that are typical of macroeconomic variables. Bańbura et al. (2015); Del Negro et al. (2020); Giannone et al. (2015); Lenza and Primiceri (2020); Ng (2021); Romer and Romer (2004) all have different orderings of variables within the VAR model. In a typical VAR model, we can treat all variables as a priori endogenous. A VAR model does not assume any direction for the relationships, but restrictions, including the exogeneity of some of the variables, may be imposed based on statistical procedures. Structural VAR analysis, then, attempts to impose and investigate whether structural economic hypotheses and variables can have contemporaneous effects on each other. In a reduced-form structural VAR, the contemporaneous effects are considered in the error term, and the occurrence of one structural shock can potentially lead to the occurrence of shocks in all error terms, thus creating contemporaneous movement in all endogenous variables.

Consider the set of $y_t = \{UNEMP_t, GDPPC_t, M2_t, M2V_t, PCECORE_t\}$; in our reduced-form VAR model, we perform:

$$y_t = \alpha + \beta_t + \sum_{k=1}^{5} \rho_k y_{t-k} + \nu_t, \qquad t = 1, ..., T, \tag{1}$$

α is the intercept, and β_t is the time trend; ρ_k represents a 5 matrix collecting the estimated coefficients, and ν_t is the idiosyncratic error term. We discuss the choice of the variables further below, but the contribution of our model is the choice of the variables and the direction of the shocks, which the VAR model as described enables us to study. The pandemic and lockdowns caused an exogenous (dramatic) unemployment shock, followed by a severe shock in the economic activity (GDP). The supply of money was raised to a historical peak, and the velocity of money followed. This has caused contemporaneous and long-term effects on core inflation. Note that a VAR model does not assume any direction for the relationships. Therefore, the coefficients pick up the dynamics of the variables over the period under study without any arbitrary restriction put on any variables. Therefore, again, this model is first estimated without any restrictions.

Only in the case of the structural shocks, u_t are identified from a Cholesky scheme restriction imposed on B such that $\nu_t = Bu_t$ or:

$$\nu_t \equiv \begin{pmatrix} \nu_t^{UNEMP} \\ \nu_t^{GDPPC} \\ \nu_t^{M2} \\ \nu_t^{M2V} \\ \nu_t^{PCECORE} \end{pmatrix} = \begin{pmatrix} b_{11} & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{pmatrix} \begin{pmatrix} u_t^{UNEMP} \\ u_t^{GDPPC} \\ u_t^{M2} \\ u_t^{M2V} \\ u_t^{PCECORE} \end{pmatrix}$$

The variables of interest in our model are: real GDP per capita (*GDPPC*), measured in chained 2012 USD; unemployment rate (*UNEMP*), measured as the number of unemployed as a percentage of the labor force; *M2* money supply (*M2*); velocity of money *M2* (*M2V*); and core inflation (*PCECORE*), measured as personal consumption expenditures excluding food and energy (chain-type price index), as a percentage change from a year ago. All of our variables are seasonally adjusted and observed at a quarterly level. For a detailed explanation of the data sources and descriptions, please see Appendix A.

Note that the VAR model will capture the co-movement of the variables over time. However, we can set a scheme for the structural shocks. The contribution of our study is the choice of the direction of the shocks, which the VAR model as described above enables us to study. By design, the first structural shock u_t^{UNEMP} stands for an exogenous (dramatic) unemployment shock caused by the pandemic and lockdowns, and u_t^{GDPPC} stands for an output shock. Note that the order of the restrictions in this analysis is specific to the current pandemic and the economic responses. By nature, monetary and fiscal policies are high-dimensional, and over the time under study, other macroeconomics indicators were affected as well. We ordered the variables from the most to least exogenous based on our theory. The dramatic shock in the unemployment rate was indeed exogenous, caused by the severe lockdowns starting in March and April 2020. u_t^{GDPPC} can be assumed to contemporaneously correspond to the unemployment shock and, along with the unemployment shock, to have contemporaneous effects on monetary policies and the supply of money. u_t^{M2} and u_t^{M2V}

refer to the shocks to money supply and velocity of money, which contemporaneously affect core inflation. Finally, $u_t^{PCECORE}$ refers to the shock to core inflation.

The main difference between the traditional VAR ordering and our VAR ordering is that we prioritized the exogenous shocks to the unemployment rate during the COVID-19 crisis. In previous recessions, such as during the Global Financial Crisis in 2008, a negative economic shock had a detrimental effect on GDP growth first. Then, the depressed economy caused an increase in the unemployment rate as the economy adjusted to the negative demand shock via employment. In contrast, we emphasize that macroeconomic variations after COVID-19 must be reorganized. U.S. states enforced unprecedented lockdown policies in March and April 2020, which had a direct impact on the labor market. Thus, this shock to the workforce was the most significant contributor to the inception and intensification of the COVID-19 recession. Our ordering of variables in the VAR model can best reflect the simultaneous effects of our variables of interest during the pandemic.

In our reduced-form structural VAR model, we estimate all the parameters from ordinary least squares (OLS) regressions. The Akaike information criterion (AIC) recommends the number of lags to consider in our model to be five. All series were seasonally adjusted, and we considered a constant and a trend in our series.

2.2. Data

We incorporated major macroeconomic indicators of the inflation suggested by the literature to understand the future direction of core prices, while considering the logical direction of the endogeneity of these indicators under the recent shocks caused by the pandemic. Then, we used a multivariate VAR model, which captures the historical dynamics of these major macroeconomic indicators of inflation and informs us about the future movements of these variables under current circumstances. We worked with the quarterly data of the unemployment rate, real GDP per capita, M2 money supply, the velocity of money, and core PCE prices. Our VAR model will provide the responses of these variables to the current shocks. The highly continuous co-variation of these series over a long period, incorporated in a VAR model that captures such variation of economic time series (without assuming any direction for causal relationship), enhances our ability to more precisely estimate and measure the magnitude of the shocks these series have encountered recently.

We used high-frequency data, observed at a quarterly level, over a long time series (1960:Q1 to 2021:Q4). The prediction of the dynamics of macroeconomic indicators at a higher frequency, especially for inflation, will help policymakers design appropriate monetary policies to circumvent the wide-ranging negative effects of the recession. The higher-frequency provides more degrees of freedom, which allows us to be more precise in understanding the relationship between inflation and the other indicators that directly affect core prices under the recent economic downturn.

As mentioned earlier, variables included in the analysis are real GDP per capita, the unemployment rate, M2 money supply, the velocity of money M2, and core inflation (for a detailed explanation of the data sources and descriptions, please see Appendix A).

Figure 2 shows the time series of GDP per capita, the unemployment rate, M2, the velocity of money, and core inflation during the sample period from 1960:Q1 to 2021:Q4. Overall, the indirect relationship between GDP and the unemployment rate, as well as money supply and the velocity of money, is evident. However, the core inflation does not follow any clear pattern. In the early 1990s, the inflation rate was at around 4%, followed by a decline to 2% until late 1999. With the beginning of the year 2000, the inflation rate in the U.S. rose again, and it reached a peak in late 2007, which is officially known as the year when the U.S. economy slowed down and entered the Great Recession. With the beginning of the crisis, inflation followed the decline and stayed below 2% until the end of the sample period. Exceptions are the years 2011 and 2012, where the inflation rate in the U.S. was at around 3%. The recent shocks in these monetary indicators had never been experienced in the last six decades in the U.S. We provide a sensitivity analysis for the period of the Great

Recession (2008:Q1 to 2009:Q2), but we should emphasize that the magnitude of the shocks are not comparable to that period.

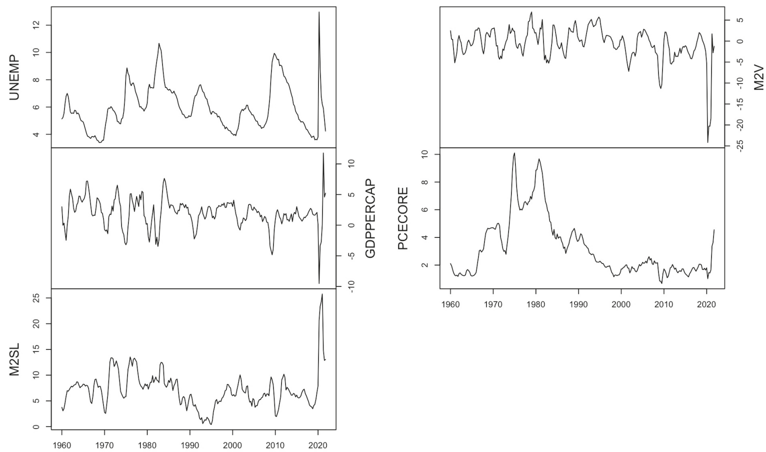

Figure 2. Unemployment rate, real GDP per capita, and M2 on the left panel and velocity of money and core inflation on the right panel for 1960:Q1 to 2021:Q4; data series are quarterly data and are seasonally adjusted.

3. Estimation Results

3.1. Main Results

Figure 3 summarizes the impulse response functions (IRFs) of the main variables of interest, core inflation, to a one standard deviation positive shock in other indicators: unemployment rate, GDP per capita, M2, and velocity of money. By design, the most significant contemporaneous response is with respect to the velocity of money. A one standard deviation positive shock in the velocity of money significantly increases core inflation. Positive shocks in M2 have a lagged positive effect on core inflation. On the other hand, in the case of recessions when there is a negative shock in the unemployment rate, following the logical trend, core inflation shows a negative downward response. Note that we worked with real GDP per capita, while the velocity of money incorporates nominal GDP.

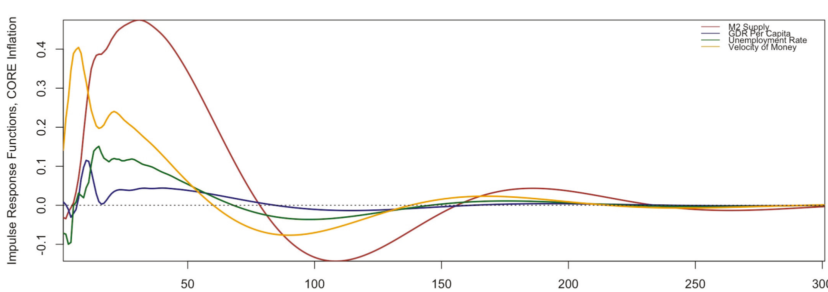

Figure 3. Impulse response functions, and core inflation with respect to a shock in other indicators.

One standard deviation of the velocity of money (3.97 percent) would cause a maximum of a 0.404 percent increase in core inflation. The second quarter of 2020 recorded the highest negative shock in the velocity of money, with 6.1-times the standard deviation. This means that a potential positive response would amount to $6.1 \times 0.404 = 2.46$ percent.

One standard deviation of M2 (3.55 percent) would cause a maximum of a 0.475 percent increase in core inflation. The first quarter of 2021 recorded the highest positive shock in M2 with 7.27-times the standard deviation. This means that a potential positive response would amount to $7.27 \times 0.475 = 3.45$ percent. Our findings suggest that, although the directions of the velocity of money and M2 shocks are opposite (as in Figure 2), even with the continuous increase in the money supply and with a recovering GDP, we expect a significant and persistent rise in core inflation during the COVID-19 crisis.

Figure 4 shows the forecast error variance decomposition (FEVD) for core inflation. The FEVD graph depicts the contribution of each individual shock as a share of the total area in a given time period. In the first quarter, we see that M2V, M2 money supply (M2SL), GDPPC, and UNEMP explain over 40 percent of the variability in core inflation, with M2V being the most significant explanatory indicator. M2V continues to play a substantial role in explaining variations in core inflation up to the ninth quarter. Beginning in the ninth quarter, we see an increasing role of M2 money supply (M2SL) as a component of the core inflation indicator, and the rising trend continues for several quarters onward. The decomposition analysis suggests that the substantial share of variations in core inflation can be explained initially by the velocity of money, then by the money supply. The result of the Granger test (order three) confirms the significance of the money supply indicator in defining core inflation with an F-statistic of 5.32 and p-value of 0.001, while for the reverse relationship, the F-statistic is 1.66 with a p-value of 0.176, indicating an insignificant relationship.

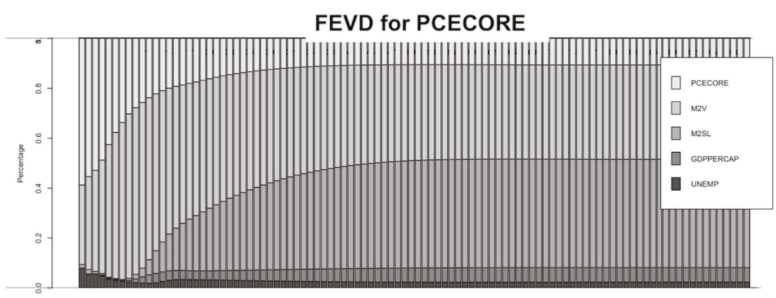

Figure 4. Forecast error variance decomposition for core inflation.

Assuming that M2V and M2 will have discretionary trends, Figure 5 shows the VAR forecast results for GDP per capita (GDPPC), the unemployment rate (UNEMP), and core inflation (PCECORE). The dashed vertical line represents the end of 2021. Hence, we are forecasting for the first quarter of 2022 and onward. Our model suggests that the unemployment rate will increase over 6 percent with a 95% confidence interval (CI). Adjustments in the labor market will continue during the first few quarters of 2022, as more people will be willing to work and actively seek employment. A gradual easement in COVID-19 health mandates in major states, such as New York relaxing mask mandates, will help contribute to an increase in the labor force. However, as more people return to the labor force, not all the newly added labor force will be able to secure employment. This is because we could experience a labor market surplus as firms may be reluctant to hire more workers at higher wages since the pandemic. As the labor market adjusts and the unemployment rate increases, our model suggests that our quarterly economic growth rate may decrease by approximately 2.5 percent.

Our estimates also indicate that core inflation will increase in the near future. For the first quarter of 2022, core inflation will rise to an average value of 5.03% (with a 95% CI of [4.53, 5.52]). For the second quarter of 2022, our model suggests that core inflation could increase to 5.45% (with a 95% CI of [4.62, 6.28]). Our forecasting analysis shows that inflation could rise as high as 8.57% (with a 95% CI of [6.02, 11.12]) in the future horizon. All of this evidence signals that the rise in inflation in the U.S. since 2021 is not "transitory", but it is relatively "persistent". Hence, the expansionary fiscal and monetary policies in 2020 will have a lingering effect on the U.S. economy unless corrected with contractionary policies.

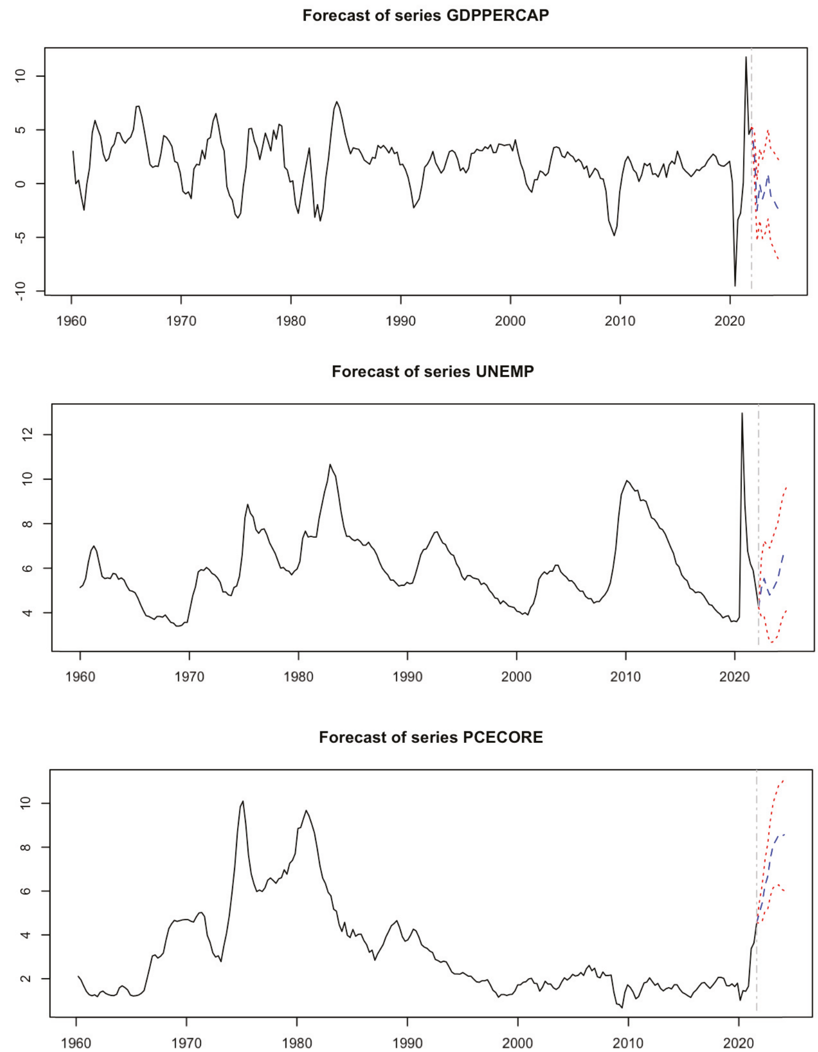

Figure 5. VAR forecast trends for GDP per capita, unemployment rate, and core inflation.

3.2. Sensitivity Analysis

Our model assumes that the disruption to the labor market during the pandemic due to stringent lockdown policies resulted in an extreme unemployment rate of 14.7 percent in April 2020. No historical lockdown policies are comparable to that of the COVID-19 crisis, which makes the pandemic period VAR analysis unique. Aastveit et al. (2017) show that the evolution of the unemployment rate during the Global Financial Crisis is different relative to its past behavior. Even though the Global Financial Crisis and COVID-19 crisis are vastly different in terms of the underlying causes, economic consequences, and policy responses, these crises share a fundamental parameter instability in the unemployment rate. Thus, we examined whether our model can provide a robust forecasting estimate of inflation during the Global Financial Crisis in 2008.[5]

We restricted our sample period from 1690:Q1 to 2009:Q3 and introduced the Global Financial Crisis shocks accordingly. Then, we forecast core inflation from 2009:Q4 to 2010:Q4. Table 1 provides the values for actual inflation, predicted inflation using our VAR model, and the absolute difference between the two parameters, which we call dispersion. We see an absolute difference of 0.3 percentage points for the first quarter. In contrast, the subsequent dispersion values are very minimal, with a maximum difference of 0.1 percentage points. Thus, the sensitivity analysis result suggests that our VAR model specification is adequate for forecasting inflation, during which there is an idiosyncratic movement in unemployment.

Table 1. Actual inflation, predicted inflation, and absolute dispersion during the Financial Crisis in 2008.

	Actual Inflation	**Predicted Inflation**	**Dispersion**
2009 Q4	1.4	1.7	0.3
2010 Q1	1.7	1.7	0.0
2010 Q2	1.6	1.5	0.1
2010 Q3	1.4	1.3	0.1
2010 Q4	1.1	1.1	0.0

4. Discussion

At the inception of our paper in mid-2021, the interest rate remained low and the Federal Reserve was cautious about raising the rates based on the "transitory" view of the rising inflation, as we discussed in Section 1. The unprecedented increase in the money supply as shown in Figure 1 and the uniqueness of the COVID-19 recession, especially with the domestic lockdowns in March and April 2020, as argued in Section 2.1, may have led to a more persistent upward shift in inflation. Our forecasts indicate that the core inflation rate will hover around a high 4% and the rate will continue to climb up in the near future. Hence, we have shown that a change in policy is necessary to correct for the upward pressure on the long-run inflation. In line with our prediction and given the persistent inflation, the Federal Reserve increased the interest rate on March 2022 by 0.25 percentage point[6].

We compared our predictions in 2022 with other predictions and examined how our predictions fared against other forecasts. In a press conference on 16 March 2022[7], Federal Reserve Chairman Jerome Powell stated that the median inflation projection of FOMC participants is 4.3 percent in 2022, 2.7 percent in 2023, and 2.3 percent in 2024. Chairman Powell added that the recent trajectory is much higher than their own projection in December 2021 and noted that the FOMC participants continue to see risks as weighted to the upside. These estimates are similar to our predictions. Furthermore, a result from the monthly Bloomberg survey of 70 economists on April 2022 shows that the average core inflation for 2022 will be approximately 4.7%.[8] Their estimate falls within our confidence interval.

The lockdowns in March and April 2020 and the consequent expansionary fiscal and monetary policies led to an unprecedented increase in the level of money supply. These government policies are not unusual as the Federal Reserve used conventional monetary tools such as lowering the interest rates and increasing asset purchases during the Global Financial Crisis (Mishkin 2009). However, the lesson from COVID-19 seems to indicate that forecasting inflation in times of a pandemic is different from in times of a financial crisis. The main difference was the lockdowns, which directly affected the unemployment rate, and our proposed model reflected this macroeconomic behavior. Hence, a major policy implication of our study is that the traditional ordering of the VAR model may not be sufficient when modeling the money supply and inflation in the current or future pandemics.

5. Conclusions

January 2022 marks the highest U.S. inflation rate in 40 years. The Federal Reserve began tightening the monetary policy in March 2022 to combat the high inflation. We showed that the traditional model of inflation forecasts may not capture all of the macroeconomic behaviors during a pandemic. The direct impact on the unemployment rate because of the lockdowns in March and April 2020 is the main difference from previous recessions. Incorporating this main difference into the model could have allowed us to realize that the COVID-19's era inflation is not transitory.

Our proposed model predicts that the annualized quarterly core inflation rate could rise to 5.03% for the first quarter of 2022 and to 5.45% for the second quarter. In a longer time horizon, we forecast that the inflation rate could reach as high as 8.57% unless corrected with appropriate monetary policies. We also showed that the high inflation after COVID-19 is not transitory, but it is persistent. That is, the recent economic recovery and the excessive supply of M2 from fiscal and monetary policies have increased the core inflation rate beyond a transitory phase.

We contribute to the literature by proposing a changed VAR model specification to forecast inflation after COVID-19. The main modification is incorporating the exogenous shocks, namely domestic lockdown policies, to unemployment during the pandemic. Our proposed VAR model reflects the real macroeconomic behaviors during the pandemic, carefully contemplates the contemporaneous effects of these indicators, and performs well in forecasting future price levels. One of the main implications of our analysis is that the macroeconomic indicators during the recent pandemic-era recession may have different parameters than those from any other recessions. Failing to re-scale these differences may have contributed to the insufficient policy responses to the inflation shocks by the Federal Reserve.

We conclude with three caveats of our research. First, we designed our VAR strategy for forecasting inflation during a pandemic time only. Second, we did not incorporate inflation expectations. Third, our approach does not incorporate up-to-date methods, such as using high-frequency movement in interest rate futures around FOMC announcement dates or using external instrumental variables to identify monetary policy shocks. We believe these are important topics for future research.

Author Contributions: Conceptualization, O.G. and S.L.; Data curation, O.G. and S.L.; Formal analysis, O.G. and S.L.; Investigation, S.L.; Methodology, O.G. and S.L.; Writing—original draft, O.G.; Writing—review and editing, S.L. All authors have read and agreed to the published version of the manuscript.

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Appendix A

The data sources employed for the analysis are summarized in Table A1.

Table A1. Descriptive statistics.

	Definition	Abbreviation Used	Source
GDP Per Capita	Measured as real gross domestic product per capita, chained 2012 USD, Quarterly, seasonally adjusted, percent change from a year ago.	GDPPERCAP	U.S. Bureau of Economic Analysis, real gross domestic product per capita, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A939RX0Q048SBEA, 1 February 2022.
Unemployment Rate	Represents the number of unemployed as a percentage of the labor force. Labor force data are restricted to people 16 years of age and older, who currently reside in 1 of the 50 states or the District of Columbia, and who are not on active duty. It is measured quarterly, and the data are seasonally adjusted.	UNEMP	U.S. Bureau of Labor Statistics, Unemployment Rate, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, 1 February 2022.
M2 Money Supply	Measured as percentage change from a year ago, seasonally adjusted quarterly data.	M2SL	Before May 2020, M2 consists of M1 plus (1) savings deposits (including money market deposit accounts); (2) small-denomination time deposits (time deposits in amounts of less than USD 100,000) less individual retirement account (IRA) and Keogh balances at depository institutions; and (3) balances in retail money market funds (MMFs) less IRA and Keogh balances at MMFs. Beginning May 2020, M2 consists of M1 plus (1) small-denomination time deposits (time deposits in amounts of less than USD 100,000) less IRA and Keogh balances at depository institutions; and (2) balances in retail MMFs less IRA and Keogh balances at MMFs. Seasonally adjusted M2 is constructed by summing savings deposits (before May 2020), small-denomination time deposits, and retail MMFs, each seasonally adjusted separately, and adding this result to seasonally adjusted M1. Board of Governors of the Federal Reserve System (U.S.), M2 Money Stock, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/M2SL, 1 February 2022.
Velocity of Money M2	Measured as percentage change from a year ago, seasonally adjusted quarterly data.	M2V	Federal Reserve Bank of St. Louis, velocity of M2 Money Stock, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/M2V, 1 February 2022.
Inflation	Personal consumption expenditures excluding food and energy (chain-type price index), as percentage change from a year ago, seasonally adjusted quarterly data.	PCECORE	U.S. Bureau of Economic Analysis, Personal Consumption Expenditures: Chain-type Price Index, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PCEPI, 1 February 2021.

Table A2 provides the descriptive statistics.

Table A2. Descriptive statistics.

	Mean	Std. Dev.	Min	Max	Median
GDP Per Capita	1.96	2.41	−9.53	11.78	2.02
Unemployment Rate	5.99	1.66	3.40	12.97	5.70
Money Supply M2	7.15	3.55	7.15	25.77	6.93
Velocity of Money M2	−0.66	3.97	−24.19	6.95	−0.34
Core Inflation	3.20	2.13	0.67	10.10	2.21

Notes

1. Siegel, Rachel. 2021. "The Fed's inflation challenge: Getting the policy and the messaging right". *Washington Post*, December 9. https://www.washingtonpost.com/business/2021/12/09/inflation-fed-transitory-powell/ (accessed on 1 March 2022).
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4. Federal Reserve. 2022. Minutes of the Federal Open Market Committee, 15–16 March 2022.
5. Note that the order of exogenous shocks in the Great Recession was different than the recent one. The VAR model captures coefficients of a system of equations in which each variable depends on the lagged values of itself and others. Therefore, the change of order will not change the forecast values. However, the potential IRFs would be sensitive to the order of restrictions one could consider.

[6] See Note 4 above.

[7] Federal Reserve. 2022. "Press Conference Transcript". 16 March. https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20220316.pdf (accessed on 1 March 2022).

[8] Pickert, Reade, and Kyungjin Yoo. 2022. "Economists Boost Inflation Expectations in Worrying Sign for Fed". *Bloomberg*, April 8. https://www.bloomberg.com/news/articles/2022-04-08/economists-boost-inflation-expectations-in-worrying-sign-for-fed (accessed on 1 March 2022).

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