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Analyzing Stock Prices to Identify Unconventional Monetary Policy Shocks Applying the SVARIH Methodology

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Highlights

- **This study seeks to establish a novel methodology for identifying unconventional monetary policy shocks with heteroskedasticity identification method in fuel-exporting countries.**
- **Stock prices variations are used to identify shocks.**
- **Policymakers can significantly influence the execution of unconventional monetary policies to alleviate the volatility of the stock market by enhancing the liquidity and dividends of the stock market.**

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Abstract

Identifying monetary policy shocks is a crucial determinant influencing stock price index in esteemed global stock exchanges. Thus, this study aims to develop a novel approach for identifying these shocks using a heteroskedasticity-based identification method. For this goal, stock price fluctuations are employed as a means of identifying the shocks. This study analyzes the dynamic responses of macroeconomic variables in fuel-exporting countries, including Colombia, Indonesia, Iran, Russia, and Saudi Arabia, to unconventional monetary policy within the SVARIH framework, utilizing stock price fluctuations from the years 2000 to 2023. The variables studied in the study include inflation, unemployment, stock prices, interest rates, and gross domestic product. The results indicate that the slope policies enacted by governments like Colombia, Iran, and Russia can facilitate economic recovery by decreasing unemployment and credit expenses. Furthermore, stock prices are demonstrated to be effective in identifying slope policy shocks. The Iranian government can implement unconventional monetary policies to enhance credit availability, hence boosting production and decreasing unemployment. Finally, given that the implications of this policy might impact individual's wellbeing, unemployment, and economic growth in aforementioned countries, it is essential to apply it for economic improvement. Policymakers can significantly influence the implementation of unconventional monetary policies to reduce stock market volatility through enhanced liquidity provision and increased equity returns.

1. Introduction

Between the 2008 financial crisis and the inflation peak in 2022, interest rates in major economies remained at historically low levels, frequently approaching the zero lower limit (ZLB) (Haldane, 2015). Central banks, rather than employing traditional monetary policy instruments, were compelled to use

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unconventional monetary policies to stimulate investment and consumption by reducing long-term rates, augmenting loans to enterprises and families, and facilitating the attainment of the inflation target (Saraceno & Tamborini, 2020). The Federal Reserve employed a range of unconventional monetary policy tools throughout the Great Recession to invigorate the economy and enhance credit and funding conditions throughout and following the financial crisis (Bernanke, 2020). Given their impact on the yield curve's slope, such measures are commonly characterized as slope policies (Eberly et al., 2019). In 2020, the Federal Reserve adjusted the federal funds rate downward, approaching the zero lower bound in reaction to the COVID-19 pandemic and implemented slope policies. While the impact of slope policies on asset prices has been extensively examined (Kuttner, 2018), its influence on the real economy remains inadequately comprehended. Gertler & Karadi (2015), Kim (2017), Eberly et al. (2019), Lakdawala (2019), and Tang et al. (2022) investigate the impact of unconventional monetary policy on asset prices employing an exogenous instrumental variable structural vector autoregression (IV-SVAR) methodology.

This research aims to demonstrate that financial markets, particularly stock prices, encompass substantial information that allows for the differentiation between policy shocks and unforeseen news regarding the economic fundamentals of financial assets, hence assessing asset stability. When monetary policy is enacted, resulting in heightened liquidity, individuals allocate their surplus funds to the stock market, so augmenting demand for equities and ultimately elevating stock prices. Numerous studies indicate that stock markets react to governmental policies and their aims. These policies also respond to economic projections and shifts in investor confidence (Ehrmann & Fratzscher, 2005; Beaudry & Portier, 2006). Consequently, incorporating stock prices enhances our information relative to methods that depend exclusively on securities returns. Monetary policy shocks can be identified through several methodologies. This study employed the heteroskedasticity identification method introduced by Rigobon (2003) and Rigobon & Sack (2004) to identify monetary policy shocks from fluctuations in stock and bond prices. In summary, it is demonstrated that the identification problem can be resolved just by employing structural shocks with heterogeneous variance, provided that structural shocks exhibit zero correlation. To maintain clarity, the endogenous variables considered were inflation, unemployment, stock prices, interest rates, GDP, and two regimes. The findings indicated that variability in stock prices enables the estimation of pertinent parameters. It should be noted that the novelty of this paper lies in the application of heteroskedasticity identification method in structural vector autoregressive approach. Variables shocks are first set at the models and then identified. This enables researchers to apply heteroskedasticity identification method more effectively and identify many shocks in the economy.

Theoretically, a negative relation exists between interest rates and stock prices; elevated interest rates result in diminished stock values through the reduction of the discounted value of expected future equity returns.

This study's methodology parallels that of Jarociński & Karadi (2020), who employ sign restrictions to distinguish between monetary policy shocks and information shocks inferred from stock price movements. Their results suggest that imposing a sign restriction on the concurrent movement of interest rates and stock prices commonly assumes that a contractionary monetary policy shock leads to higher bond yields and lower stock prices, while a positive information shock is associated with concurrent increases in both bond yields and stock prices.

The subsequent sections are arranged as follows: Section Two delineates the literature review, Section three elucidates the theoretical foundations, Section Four outlines the methodology, Section 5 details the modelling and model specification, and the concluding section articulates the results.

2. Literature Review

Hohberger et al. (2023) compared models for the Eurozone and the United States to investigate the influence of unconventional monetary policy shocks and showed that this type of policy has expansionary effects on variables such as output growth and inflation dynamics. Conventional monetary policy manages and modifies policy interest rates, whereas unconventional monetary policies influence the economy through alternative mechanisms (Gertler & Karadi, 2015). Forward guidance, as an unconventional monetary policy instrument, pertains to the dissemination of information regarding the anticipated trajectory of interest rates or economic conditions (Campbell et al., 2012). Quantitative easing, as an additional instrument of this policy, effectively enhances economic circumstances by regulating the supply of long-duration assets while ensuring adequate liquidity in credit channels (Stroebel & Taylor, 2012; Hanson et al., 2018). Gilchrist et al. (2015) identify monetary shocks utilizing a two-dimensional framework. For instance, by analyzing fluctuations in the response of the 2-year Treasury yield to policy announcements and in variations in the 10-year yield uncorrelated with short-term rate changes, they demonstrate that unconventional monetary policy is more efficient than conventional monetary policy in diminishing real borrowing costs. Neuhierl & Weber (2021) employ a case study methodology to demonstrate that unconventional monetary policy exerts a short-term impact on financial prices. Lütkepohl et al. (2021) demonstrate that heteroskedasticity identification is extensively employed in structural vector autoregressive analysis for models featuring two states characterized by swing-state dynamics. The core idea behind this identification strategy is that, if the variances of structural shocks are time-varying and exhibit heterogeneous changes across different shocks, this feature can be leveraged to achieve structural shock identification. The primary benefit of heteroskedasticity identification is the complete availability of data for the identification process. Eberly et al. (2019) show that, in response to the global financial crisis, the federal government reduced the policy interest rate and implemented unconventional monetary policy measures to stimulate economic activity. Mertens & Ravn (2013) demonstrated the impact of monetary policy through a structural vector autoregressive methodology utilizing an external instrumental variable. Furthermore, khadem Nematollahy et al. (2023) examined the impacts of demand, supply, exchange rate, and unconventional monetary policy (UMP) shocks on GDP, inflation, exchange rate, and interest rate in Iran Using sign-restriction, short-run zero-restriction, and long-run zero-restriction inside vector autoregressive with data spanning from 1961-Q1 to 2021-Q1. Zamanzadeh et al. (2020) investigated the impact of monetary and fiscal policy on unemployment by modelling unemployment duration using the Phillips curve, utilizing data from 1997 to 2017 and employing the Bayesian panel data approach with heterogeneous coefficients. Research evidence indicates that expansionary monetary policy reduces the length of unemployment. Rasouli et al. (2020) examined the impact of monetary and fiscal policies on the unemployment rate utilizing Bayesian dynamic models (TVP-FAVAR, TVP-DMA) and demonstrated that monetary policies influence the unemployment rate through alterations in liquidity and exchange rates, while fiscal policies affect the unemployment rate by modifying government expenditure. Salmani Bishak et al. (2015) assessed the impact of monetary and fiscal policy shocks on the stock market utilizing seasonal data from 1991 to 2010 and the SVAR methodology. They demonstrated that monetary policy shocks, namely money supply, positively influence the rise of the stock price index over both short-term and long-term horizons. Consequently, the impact of monetary policy is more immediate than that of fiscal policy. Arshadi (2012) analyzed the impact of optimum monetary policy on inflation and unemployment under uncertain conditions, utilizing data from 1959 to 2007 and the VAR methodology, and concluded that Iranian policymakers must consider fluctuations in inflation and unemployment in their decision-making processes. Nonejad et al. (2012) employed a vector autoregressive model utilizing seasonal data from 1990 to 2008, with nominal and real stock price data, demonstrating that monetary policy positively influences the stock price index. Finally, considering the significance of unconventional monetary policy in enhancing wellbeing, diminishing unemployment, and fostering economic growth, extensive research has been undertaken on this strategy across various nations. Considering the limited application of unconventional monetary policy in Iran, it is crucial to assess the impact of this policy using indicators such as stock prices in the field of economics. Ioannidis & Kontonikas (2008) investigated the impact of monetary policy on stock returns in 13 OECD countries over 1972–2002 and illustrated that monetary policy shifts significantly affect stock returns. This study analyzes the dynamic responses of macroeconomic variables in Fuel-exporting countries, including Colombia, Indonesia, Iran, Russia, and Saudi Arabia, to unconventional monetary policy, utilizing stock price fluctuations within the SVARIH framework, incorporating inflation, unemployment, stock prices, interest rates, and GDP variables. This paper aims to demonstrate that unconventional monetary policies in Iran, while primarily executed as balance sheet policies that enhance financial and macroeconomic stability through liquidity provision and bond purchases, also significantly bolster financial market stability when applied as monetary policy.

3. The Theoretical Framework

The theoretical foundations of unconventional monetary policy via the dual instruments of interest rates and stock prices can be delineated in three sections: 1- The function of monetary interest rates on capitalist system crises. 2- Mechanisms of effect of unconventional monetary policies and the impact of populism or the people's party on unconventional monetary policy. 3- The impact of unconventional monetary policies on asset markets.

3.1 The function of monetary interest rates on the capitalist system crises

Monetary interest rates significantly influence output levels and employment, while also precipitating crises and engendering uncertainty and inflation. They also inhibit the economy from achieving efficient resource allocation and a stable equilibrium. This phenomenon occurs within the capitalist system, wherein banks generate substantial liquidity through elevated interest rates on several loan categories, ultimately precipitating economic crises and imbalances. This mechanism allows commercial banks to generate credit money, so augmenting the buyer's purchasing power. Conversely, they cultivate the money illusion. A significant portion of depositors in commercial banks perceives their funds as akin to cash available for use. Conversely, many believe that these funds have been allocated for investing purposes. The contrasting sentiments of possessing and lacking financial resources have prompted depositors to withdraw funds from banks, resulting in a banking crisis. Ultimately, banks may become insolvent, resulting in stockholders forfeiting their capital and depositors losing their investments. A crisis impacts not only other banks but also financial markets and, eventually, the entire economy. Systemic risk, global shocks, and exchange rate volatility in nations are variables influencing banking crises (Shajari & Mohebikhah, 2010). Moreover, Keynes (1936), Allais (1974), Lerner (1959), Tobin (1967), and Friedman (1969) have demonstrated that the persistence of monetary interest rates has several adverse effects on the economy, resulting in inefficiencies in resource allocation and contributing to unemployment. Consequently, it is essential to mitigate the potential for crises and volatility in global financial markets through appropriate policies. In this context, banks across many nations have endeavored to offer support to consumers and enterprises by lowering lending rates and to promote economic production by incentivizing investment to mitigate the adverse impacts of recession. At present, interest rates in Japan have attained zero. The United States and European nations are endeavoring to lower interest rates. Turkey is among the nations that have achieved notable success in managing inflation and enhancing economic growth through the reduction of interest rates in recent decades. (Mohammadi & Mahmoudi, 2017).

3.2 Mechanisms of effect of unconventional monetary policies and the impact of populism or the people's party on unconventional monetary policy

Unconventional monetary policy employs a range of instruments. Cole (2021) underscores forward guidance as a crucial instrument of this policy. Gertler & Karadi (2011) and Sims et al. (2023) regard quantitative easing as a significant instrument for executing unconventional monetary policy. This policy was established to address the elevated inflation rate post covid-19, aiming to enhance liquidity for borrowing in the market (Cole & Huh, 2024). The mechanisms by which unconventional monetary policy instruments influence the economy include the income and wealth distribution channels, together with their subdivisions illustrated in the figure below (Davtyan, 2023).

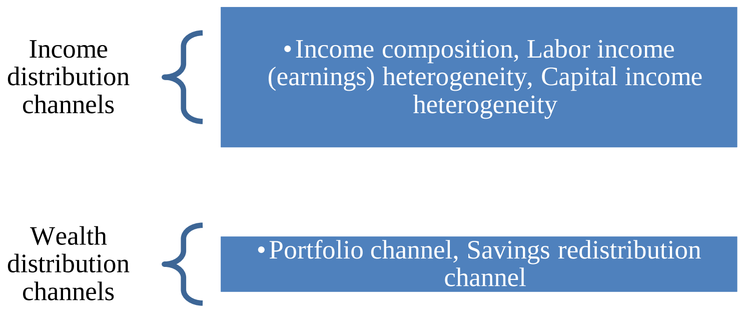

Figure 1. channels of unconventional monetary policy
***Source**: (Davtyan, 2023)*

Income composition denotes the diversity of primary income sources, whether derived from labor or capital, distributed among families within a society. Labor income heterogeneity denotes that the earnings of the lowest socioeconomic group are susceptible to variations in economic cycles. Capital income heterogeneity signifies that asset returns are influenced by monetary policy and that the structure of household asset portfolios varies throughout the distribution. The portfolio channel pertains to household wealth, encompassing capital assets and real estate. The savings redistribution channel demonstrates that households possess varying levels of savings and are influenced by unconventional monetary policy in diverse manners. (Davtyan, 2023).

The conservative party, referred known as populism or the people's party, has gained traction owing to the global financial crisis and media influence. Populist politicians have employed unconventional monetary policies and exhibited more risk taking. A notable instance of populism is the autonomy of the central bank, which formulates monetary policy independently of political influence and aims to establish financial stability through several strategies (Haynes, 2023).

3.3 The impact of unconventional monetary policies on asset markets

Numerous approaches exist to analyze the implications of unconventional monetary interventions for financial market behavior. Given that asset prices respond to unconventional monetary policy announcements, researchers frequently employ methodologies like the event study method to analyze the effects of this policy on asset prices (Bhattarai and Neely, 2020). To this end, they regress the asset return on the unconventional monetary policy announcement's surprise component.

$$R_{it} = a + bsurprise_{it} + \varepsilon_{it} \tag{1}$$

where R_{it} represents the asset return and $surprise_{it}$ denotes the shock component of the monetary policy announcement. Indeed, unconventional monetary policy influences asset valuations. It diminishes both domestic and international returns. Asset purchases influence stock prices and, via expansionary monetary policy, impact economic activity by elevating stock prices and enhancing balance sheets, hence fostering increased consumption and investment while mitigating asymmetric information issues in lending markets. Unconventional monetary policy influences international asset movements and channels financial resources to emerging markets (Bhattarai & Neely, 2020).

The percentage change in stock prices is represented by SP_{it}, whereas the percentage change in long-term returns is indicated by r_{it}. Equation (2) disaggregates the variation in stock prices into two disturbances: ε_{1it}, which represents fluctuations in investor sentiment on the economy, and ε_{2it}, which denotes real or anticipated alterations in monetary policy.

$$SP_{it} = \gamma\varepsilon_{1it} + \varepsilon_{2it} \tag{2}$$

The identification of ε_{2it} is contingent upon fluctuations in financial prices. The positive or negative impact may stem from unexpected announcements regarding government policy or abrupt shifts in investor's expectations about such policy, thus influencing bond prices. Stock prices may also reflect non-monetary factors (e.g., oil price volatility, geopolitical risks), especially in fuel-exporting countries. it also should be noted that stock markets respond to both conventional and unconventional monetary policy actions. As fuel-exporting countries have dynamics and High exposure to global financial cycles, these countries often experience capital inflows or outflows based on global liquidity conditions shaped by major central bank's policies. Thus, stock prices are a relevant indicator for the monetary policy of oil-exporting countries for several reasons:1. Oil price sensitivity and economic stability 2. Influence on domestic credit conditions 3. Policy responses to currency fluctuations 4. Economic diversification and structural change. In other words, Stock prices in oil-exporting countries provide valuable insights into the economic conditions influenced by fluctuations in global oil prices. They serve as an early indicator of how monetary policy decisions are affecting economic sentiment, inflation expectations, and credit conditions. By analyzing stock prices, central banks can better calibrate their monetary policy to maintain stability in an economy that is highly vulnerable to oil price shocks.

Given that a primary objective of monetary policy is to stabilize financial markets, Iran has employed this approach in recent years through both conventional and unconventional methods. The unconventional monetary policies in Iran, referred to balance sheet policies, aimed to achieve two objectives: 1) Financial stability, encompassing the provision of liquidity to credit markets and the facilitation of foreign exchange liquidity to domestic markets. 2) Macroeconomic stability, encompassing bond purchases, extensive foreign exchange intervention, and loan provision to the private sector, has been prioritized by the government in recent years. Conventional monetary policy often employs mechanisms such as the legal reserve ratio, credit limits, and central bank borrowing to regulate the growth rate of the money supply (Hemmati, 2010).

4. Research Methodology

Rigobon (2003) and Rigobon & Sack (2004) introduced heteroskedasticity identification to identify simultaneous equations through variations in the variance of structural shocks. This study employs an identification method utilizing five variables, including fluctuations in stock prices, inflation, unemployment rate, interest rate, and GDP. A reduced-form vector autoregressive model of dimension K with P delays for various time intervals is proposed as follows:

$$y_{it} = v + A_{i1}y_{it-1} + \cdots + A_{ip}y_{it-p} + u_{it} \tag{3}$$

v represents the intercept, while $A_{i1}, \dots, A_{ip}$ denote the coefficient matrices that satisfy the stability condition.

$$\det\left(I_K - A_{i1}z - \cdots - A_{ip}z^{ip}\right) \neq 0 \;\; for\ |z| \leq 1 \tag{4}$$

u_{it} constitutes white noise and is independent of u_{is}. $E(u_{it}) = 0$ and the covariance matrices are articulated as follows:

$$E(u_{it}\acute{u}_{it}) = \begin{Bmatrix} \Sigma_{i1} \;\; for\ t \in \; T_{i1} = (1, \dots, T_{1it}) \\ \Sigma_{i2} \; for\ t \in \; T_{i2} = (T_{i1+1}, \dots, T) \end{Bmatrix} \tag{5}$$

In the aforementioned equations, T denotes the sample size and i signifies the cross sections. The model errors exhibit heteroscedasticity, resulting in a transition in the covariance matrix from Σ_{i1} to Σ_{i2} at time T_{i1+1}. T_{i1} encompasses a portion of the period, while T_{i2} encompasses another portion of the period. The covariance matrices Σ_{i1} and Σ_{i2} are expressed in the following manner:

$$\Sigma_{i1} = B_i\acute{B}_i \qquad\qquad \Sigma_{i2} = B_i\Lambda_i\acute{B}_i \tag{6}$$

In the aforementioned equations, $\Lambda_i = \mathrm{diag}(\lambda_{i1}, \dots, \lambda_{ik})$ represents a $k \times k$ diagonal matrix with positive diagonal entries, while B_i denotes a $k \times k$ non-singular matrix (Lütkepohl, 2013). A fundamental assumption in structural vector autoregressive models is that only the variations of the shocks alter, while the response of the variables remains constant. This is accomplished by deriving structural shocks from reduced-form errors, where $\varepsilon_{it} = {B_i}^{-1}u_{it}$, with B_i representing the instantaneous effects matrix of the shocks, and the covariance matrices of the structural shocks are articulated as follows:

$$E(\varepsilon_{it}\acute{\varepsilon}_{it}) = \begin{Bmatrix} I_{ik} & for\ t \in T_{i1} \\ \Lambda_i & for\ t \in T_{i2} \end{Bmatrix} \tag{7}$$

Structural shocks are concurrently uncorrelated with both oscillatory regimes. The SVAR(p) model is derived by replacing structural errors with reduced form errors.

$$y_{it} = v + A_{i1}y_{it-1} + \cdots + A_{ip}y_{it-p} + B_i\varepsilon_{it} \tag{8}$$

In the aforementioned model, the B_i represent the eigenvectors that require estimation, hence resolving the identification issue in the SVAR(p) model. The uniqueness of the matrix B_i is attained when the diagonal elements of the matrix Λ_i are arranged in descending order, thereby precluding the potential reversal of the matrix's signs. Consequently, the null hypothesis regarding the absence of identification is evaluated against the alternative hypothesis.

$$H_0: \lambda_{is+1} = \lambda_{is+2} = \cdots = \lambda_{is+r} (= \lambda_0) \quad H_1: \lambda_{is+1} \neq \lambda_{is+2} \neq \cdots \neq \lambda_{is+r} (\neq \lambda_0) \tag{9}$$

Acceptance of the null hypothesis indicates the absence of identification. Rejection of the null hypothesis indicates that the λs are unequal, hence identifying the structural parameters via heteroskedasticity. Lütkepohl & Milunovich (2016) employed an alternative approach to evaluate vector autoregressive models with conditionally heterogeneous errors. Lewis (2018a) introduced the rank test for identification via heteroskedasticity. Furthermore, Wozniak & Droumaguet (2015) and Lütkepohl & Wozniak (2020) employed Bayesian techniques to evaluate identification via heteroskedasticity in their models. The heteroskedasticity identification method highlights the variation in the relative significance of shocks. Breitung et al (2004), Lütkepohl (2005), and Kilian & Lütkepohl (2017) identified structural shocks by applying long-run restrictions. Chen & Netsunajev (2016) utilized seasonal data from 1970 to 2007 to identify GDP and unemployment shocks via heteroskedasticity.

4.1 Identifying monetary policy shocks with heteroskedasticity

This section presents the variables under investigation in a matrix format utilizing the heteroscedasticity method, along with their corresponding shocks. The equation is articulated as follows:

$$\begin{bmatrix} 1 & b_{12} & b_{13} & b_{14} & b_{15} \\ a_{21} & 1 & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & 1 & b_{34} & b_{35} \\ b_{41} & b_{42} & b_{43} & 1 & b_{44} \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 \end{bmatrix} \begin{bmatrix} inf_{it} \\ unm_{it} \\ sp_{it} \\ gdp_{it} \\ r_{it} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \\ \varepsilon_{3it} \\ \varepsilon_{4it} \\ \varepsilon_{5it} \end{bmatrix} \tag{10}$$

In a broader context, the b_i represent the eigenvectors that require estimation, and the identification issue must be addressed within the SVAR(p) model. The parameters in B are presumed to be stable across regimes, which, as noted by Rigobon (2003), is a crucial assumption for finding shocks with heteroskedasticity. Moreover, the instrument employed in the structural vector autoregressive model is estimated using the instrumental variable within the model, which is correlated with the monetary policy shock yet orthogonal to other structural shocks.

$$Cov\left(Z_{it}\varepsilon_{it}{}^{policy}\right) \neq 0 \quad (11)$$

$$Cov(Z_{it}\varepsilon_{it}{}^{other}) = 0 \quad (12)$$

5. Modeling and Experimental Analysis

This part will first present the research data, followed by the estimation of the empirical model utilizing the research information and data. The findings of the model estimation have been thoroughly analyzed.

5.1 model specification

The study seeks to analyze the dynamic reactions of macroeconomic variables in Fuel-exporting countries to unconventional monetary policy within the SVARIH framework (structural vector autoregressive with heteroskedasticity identification method), utilizing fluctuations in stock prices. Annual data on inflation, unemployment, stock prices, interest rates, and gross domestic product are utilized for this purpose. Data regarding the variables are extracted from the World Bank. The Fuel-exporting countries examined are Colombia, Indonesia, Iran, Russia, and Saudi Arabia.

$$y_{it} = v + A_{i1}y_{it-1} + \cdots + A_{ip}y_{it-p} + B_i\varepsilon_{it} \quad (13)$$

The vector $y_{it} = (inf_{it}, unm_{it}, sp_{it}, r_{it}, gdp_{it})$ and $A_{it} = (A_{i1}, A_{i2}, \ldots, A_{ip})$ constitute the coefficient matrix of the structural form. inf_{it} denotes inflation, unm_{it} signifies unemployment, sp_{it} represents stock price, r_{it} indicates interest rate, and gdp_{it} refers to gross domestic product. i denotes the cross sections or countries being examined. t denotes the time interval under examination. Inflation data is derived from the price index, unemployment is measured as the total unemployment percentage of the labor force, stock price is based on the total value of shares traded, interest rate is determined by the deposit interest rate, and GDP is calculated at base year prices of 2015. Moreover, estimation in SVARIH is based on the optimization of a likelihood function in models where the VAR-parameters have been concentrated out.

5.2 Analysis of findings

This research analyzes data on inflation, unemployment, stock prices, interest rates, and GDP for Colombia, Indonesia, Iran, Russia, and Saudi Arabia from the years 2000 to 2023, identifying these variables through heteroscedasticity with unconventional monetary policy. The identification results are dictated by heteroscedasticity during a 24-year period. The logarithm of the variables has been utilized in the estimation. A unit root test is initially conducted to analyze the relationships among the variables. Table 1 presents the stationary state of the variables.

Table 1. Results of stationary test

Indonesia			Colombia		
Stationary rank	probablity	variables	Stationary rank	probablity	variables
I(0)	0.002	linf	I(0)	0.06	**linf**
I(0)	0.06	lunm	I(0)	0.03	**lunm**
I(0)	0.009	lsp	I(0)	0.05	**lsp**
I(0)	0.03	lr	I(0)	0.04	**lr**
I(0)	0.01	lgdp	I(0)	0.0006	**lgdp**
	Russia			Iran	
I(0)	0.01	linf	I(0)	0.002	**linf**
I(0)	0.06	lunm	I(0)	0.005	**lunm**
I(0)	0.001	lsp	I(0)	0.001	**lsp**
I(0)	0.10	lr	I(0)	0.01	**lr**
I(0)	0.03	lgdp	I(0)	0.01	**lgdp**
				Saudi Arabia	
			I(0)	0.01	**linf**
			I(0)	0.06	**lunm**
			I(0)	0.0006	**lsp**
			I(0)	0.06	**lr**
			I(0)	0.006	**lgdp**

Source: *research findings*

Two models were estimated for all nations. The initial model analyzed the variables of stock prices, interest rates, and inflation. The second model analyzed stock prices, GDP, and unemployment. To estimate the models for the five countries, two matrices, a and b, were initially defined, followed by the establishment of a regime variable defined according to the Sudden changes in the variables (the volatilities of the shocks in models have changed in the years and containing values of 1 and 2). Matrix a is characterized as a 3x3 identity matrix, while matrix B is defined by a more intricate configuration containing numerous zeros. The regime variable identifies the variable whose observations define the oscillatory regimes. The SVARIH-Lütkepohl approach is confined to two oscillatory states and is represented numerically by the numbers 1 and 2. Both values were utilized in the calculated sample. The models were first generated without accounting for heteroskedasticity identification method and utilized a structural vector autoregressive technique. This model's short-term parameter estimations suggest that the research analyses the behavior of certain variables in the short term and forecasts future behavior based on current data. Log-likelihood values were computed for the models throughout several iterations (ranging from 0 to 6). Log-likelihood is a statistical metric that assesses the efficacy of a model in elucidating observable data. Elevated values signify a superior alignment of the model with the data, indicating that the model elucidates the data with greater precision. The values commence at a specific number for iteration 0 and vary with each subsequent iteration. The values enhance (decrease in negativity or increase in positivity) with the progression of iterations. This signifies that the model is improving its ability to elucidate the data with each iteration. Implementing a structural vector autoregressive model illustrates the intertemporal relationships among several variables. Tables 2-11 delineate the methodology for estimating parameters within a model utilizing matrices and log-likelihood values. The structural vector autoregression approach provides a framework for analyzing relationships among various time series data. Every portion of the tables include distinct coefficients and their corresponding data. In matrix a, numerous coefficients are bound to zero, indicating they are fixed and remain unchanged. This is frequently executed to streamline the model, as these variables exert negligible influence. A probability value below 0.05 for the observed relationship is typically regarded as statistically significant. Certain coefficients are designated as constrained, indicating they are set at a specified value (e.g., 0 or 1) during the study. The log-likelihood probability value obtained through the structural vector autoregressive method with heteroscedasticity identification surpasses that of the method without such identification, indicating superior explanatory power and accuracy of the former model. The significancy of the model in the structural vector autoregressive framework with heteroscedasticity identification surpasses that of the model without such identification.

Table 2. Results of the first and second models for Colombia

first model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 2.595	Log-likelihood quantity: 0.347
The number of Iteration in Log-likelihood quantity:12	The number of Iteration in Log-likelihood quantity:6
second model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 73.32	Log-likelihood quantity: 70.4004
The number of Iteration in Log-likelihood quantity:13	The number of Iteration in Log-likelihood quantity:7

Source: *research findings*

Table 3. Results of the first and second models for Colombia (Structural vector autoregressive with heteroskedasticity identification method)

Estimation of the second model b matrix with lsp lgdp lunm variables:			Estimation of the first model b matrix with lsp lr linf variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.298	1-1	0.000	0.276	1-1
0.388	0.004	1-2	0.46	0.034	1-2
0.393	-0.0183	1-3	0.76	0.016	1-3
-	0	2-1	-	٠	2-1

0.000	0.028	2-2	0.000	0.232	2-2
0.000	-0.099	2-3	0.000	0.218	2-3
-	0	3-1	-	٠	3-1
-	0	3-2	-	٠	3-2
0.000	0.052	3-3	0.000	0.1519	3-3

Source: *research findings*

Tables 2-3 demonstrate that the adoption of the structural vector autoregressive model with heteroscedasticity identification yields higher and more precise log-likelihood probability values. The 12th and 13th iterations of the first and second models yield positive log-likelihood probabilities of 2.595 and 73.32, respectively, suggesting that the model incorporating heteroscedasticity is beginning to align more effectively with the data. The positive and significant coefficients of 1-1, 2-2, and 3-3 for stock prices in both models indicate that the unconventional monetary policy shock is anticipated to have a beneficial influence on stock prices in Colombia.

Table 4. Results of the first and second models for Indonesia

first model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 19.586	Log-likelihood quantity: 18.019
The number of Iteration in Log-likelihood quantity:11	The number of Iteration in Log-likelihood quantity:6
second model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 111.71	Log-likelihood quantity: 105.352
The number of Iteration in Log-likelihood quantity:12	The number of Iteration in Log-likelihood quantity:8

Source: *research findings*

Table 5. Results of the first and second models for Indonesia (Structural vector autoregressive with heteroskedasticity identification method)

Estimation of the second model b matrix with lsp lgdp lunm variables:			Estimation of the first model b matrix with lsp lr linf variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.161	1-1	0.000	0.207	1-1
0.087	0.004	1-2	0.011	-0.080	1-2
0.401	0.013	1-3	0.005	-0.179	1-3
-	0	2-1	-	0	2-1
0.000	0.0129	2-2	0.000	0.126	2-2
0292	-0.017	2-3	0.027	0.106	2-3
-	0	3-1	-	0	3-1
-	0	3-2	-	0	3-2
0.000	0.072	3-3	0.000	0.267	3-3

Source: *research findings*

The findings from Tables 4-5 demonstrate that when the models are estimated using the structural vector autoregressive model with heteroscedasticity identification, the log-likelihood probability values are greater and more precise. The positive and significant coefficients of 1-1, 2-2, and 3-3 for stock prices in both models indicate the estimation of unconventional monetary policy shocks and their favorable impact on stock prices in Indonesia. This indicates that this variable positively influences production enhancement and inflation reduction, as demonstrated in the second model of Table 5.

Table 6. Results of the first and second models for Iran

first model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 26.825	Log-likelihood quantity: 22.968
The number of Iteration in Log-likelihood quantity:36	The number of Iteration in Log-likelihood quantity:8
second model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 68.751	Log-likelihood quantity: 68.111
The number of Iteration in Log-likelihood quantity:14	The number of Iteration in Log-likelihood quantity:8

Source: *research findings*

Table 7. Results of the first and second models for Iran (Structural vector autoregressive with heteroskedasticity identification method)

Estimation of the second model b matrix with lsp lgdp lunm variables:			Estimation of the first model b matrix with lsp lr linf variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.513	1-1	0.000	0.424	1-1
0.348	0.005	1-2	0.113	0.014	1-2
0.003	-0.039	1-3	0.000	0.3003	1-3
-	0	2-1	-	0	2-1
0.000	0.026	2-2	0.000	0.0393	2-2
0.606	0.006	2-3	0.000	0.1657	2-3
-	0	3-1	-	0	3-1
-	0	3-2	-	0	3-2
0.000	0.052	3-3	0.000	0.331	3-3

Source: *research findings*

Table 6 demonstrates that the application of the structural vector autoregressive model with heteroscedasticity identification for Iran yields larger and more precise log-likelihood probability values with increased estimation iterations. After 36 and 14 iterations in the first and second models, the log-likelihood probabilities stabilize at 26.825 and 68.751, respectively, indicating that the heteroscedasticity identification model is appropriate for effectively fitting the data. Furthermore, Table 7 demonstrates positive and significant coefficients for stock prices in both models. The second model, accounting for heteroscedasticity, indicates that an increase in stock prices adversely and significantly impacts unemployment while positively influencing GDP.

Table 8. Results of the first and second models for Russia

first model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 0.167	Log-likelihood quantity: -3.119
The number of Iteration in Log-likelihood quantity:12	The number of Iteration in Log-likelihood quantity:7
second model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 80.139	Log-likelihood quantity: 73.65
The number of Iteration in Log-likelihood quantity:61	The number of Iteration in Log-likelihood quantity:8

Source: *research findings*

Table 9. Results of the first and second models for Russia (Structural vector autoregressive with heteroskedasticity identification method)

Estimation of the second model b matrix with lsp lgdp lunm variables:			Estimation of the first model b matrix with lsp lr linf variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.254	1-1	0.000	0.263	1-1
0.005	0.0114	1-2	0.003	-0.082	1-2
0.469	-0.0122	1-3	0.294	-0.0415	1-3
-	0	2-1	-	0	2-1
0.000	0.0162	2-2	0.000	0.152	2-2
0.000	-0.0694	2-3	0.893	0.008	2-3
-	0	3-1	-	0	3-1
-	0	3-2	-	0	3-2
0.000	0.079	3-3	0.000	0.344	3-3

Source: *research findings*

The findings in Tables 8-9 demonstrate that when the models are estimated using the structural vector autoregressive model with heteroscedasticity identification, the log-likelihood probability values transition from negative to positive and are achieved with greater precision. Both models yield positive and significant coefficients for stock prices in Russia, indicating that unconventional monetary policy is accurately identified. The second model in Table 9 demonstrates that stock prices exert a positive and significant influence on GDP while negatively impacting unemployment.

Table 10. Results of the first and second models for Saudi Arabia

first model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: -5.849	Log-likelihood quantity: -8.715
The number of Iteration in Log-likelihood quantity:14	The number of Iteration in Log-likelihood quantity:5
second model	
Structural vector autoregressive with heteroskedasticity identification method	Structural vector autoregressive without heteroskedasticity identification method
Log-likelihood quantity: 85.307	Log-likelihood quantity: 84.333
The number of Iteration in Log-likelihood quantity:18	The number of Iteration in Log-likelihood quantity:7

Source: *research findings*

Table 11. Results of the first and second models for Saudi Arabia (Structural vector autoregressive with heteroskedasticity identification method)

Estimation of the second model b matrix with lsp lgdp lunm variables:			Estimation of the first model b matrix with lsp lr linf variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.264	1-1	0.000	0.214	1-1
0.808	0.0012	1-2	0.847	-0.009	1-2
0.006	0.039	1-3	0.016	-0.228	1-3
-	0	2-1	-	0	2-1
0.000	0.028	2-2	0.000	0.376	2-2
0.001	-0.039	2-3	0.294	0.127	2-3
-	0	3-1	-	0	3-1
-	0	3-2	-	0	3-2
0.000	0.0318	3-3	0.000	0.436	3-3

Source: *research findings*

Furthermore, the results presented in Tables 10-11 indicate that the log-likelihood probability values and the positive, significant coefficients of stock prices have been derived with enhanced precision. All models employing the structural vector autoregressive framework with heteroscedasticity identification have executed simultaneous parameter estimation, indicating that the model has assessed the interactions among variables at a concurrent time point. Table 11 in Section 1-3 illustrates the simultaneous impact of stock prices on inflation reduction in Saudi Arabia. The log-likelihood probability quantifies the model's effectiveness in elucidating the observed data. Elevated values signify superior fitness. As the number of iterations increases, as demonstrated in Tables 2, 4, 6, 8, and 10, the log-likelihood probability fitness values improve, with each iteration surpassing its predecessor. Furthermore, the convergence of the models indicates that the identification process persists through several iterations, with log-likelihood values progressively rising.

Table 12. Results of robustness tests

Robustness tests for Colombia					
Estimation of the second model b matrix with lsp lgdp variables:			Estimation of the first model b matrix with lsp lr variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.319	1-1	0.000	0.283	1-1
Robustness tests for Indonesia					
Estimation of the second model b matrix with lsp lgdp variables:			Estimation of the first model b matrix with lsp lr variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.218	1-1	0.000	0.207	1-1
Robustness tests for Iran					
Estimation of the second model b matrix with lsp lgdp variables:			Estimation of the first model b matrix with lsp lr variables:		
				Second model	First model
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.472	1-1	0.000	0.511	1-1
Robustness tests for Russia					
Estimation of the second model b matrix with lsp lgdp variables:			Estimation of the first model b matrix with lsp lr variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.254	1-1	0.000	0.290	1-1
robustness tests for Saudi Arabia					
Estimation of the second model b matrix with lsp lgdp variables:			Estimation of the first model b matrix with lsp lr variables:		
Second model			First model		
probability	Coefficient	Matrix dimension	probability	Coefficient	Matrix dimension
0.000	0.276	1-1	0.000	6.16	1-1

Source: *research findings*

In Table 12, to assess the robustness of our model, we excluded *linf* from the first model and *lunm* from the second. In fact, robustness tests, including variable exclusions, sample period changes and model variations, were performed and these tests confirmed that the results remained consistent. It should also be noted that the exclusion of oil prices and global financial conditions from the SVARIH model could bias the results, and this is a limitation of the SVARIH approach used.

6. Discussion and Conclusion

This study aimed to estimate and identify unconventional monetary policy shocks via stock prices utilizing a structural vector autoregressive model with heteroscedasticity identification. The results are concisely summarized and delineated below.

A: The log-likelihood values illustrate the significance of iteration in enhancing model fit and comprehending the relationships among various time series data. Consequently, Tables 2, 4, 6, 8, and 10 present the number of iterations of the log-likelihood values, reflecting the stages in the optimization process aimed at refining the model's alignment with the data. For instance, reiterating steps 0 to 6 in the first model for Colombia presented in Table 2, where the log-likelihood probability is non-concave at step 0, signifies that the model's fit was exceedingly inadequate in the initial phase, as evidenced by a minimal log-likelihood probability. This instability in the optimization process necessitated iterations until positive and improved fitting values were achieved.

B: Tables 3-5-7-9-11 demonstrate that the unconventional monetary policy shock to stock prices significantly influences production enhancement, inflation reduction, and unemployment decrease. The significance of models in the structural vector autoregressive framework with heteroscedasticity identification surpasses that of models without such identification. The results were similar to the analysis by Ma (2024) showed that stock prices identified by heteroscedasticity, indicating that the unconventional monetary policies of the US federal government have effectively diminished unemployment and fostered economic recovery.

C: It is important to highlight that the short-run parameters were estimated in the structural vector autoregressive model lacking identification with heteroscedasticity, while the simultaneous parameters were estimated in the structural vector autoregressive model with identification incorporating heteroscedasticity.

D: The stock prices can affect aggregate demand and supply affecting the cost of credit of firms. An increase in the stock price of the firm increases its net equity. As a result, credit becomes more easily available for the firm, stimulating investment demand. This is the aggregate demand effect of an increase in the stock price.

E: Finally, it is important to mention that the SVARIH-Lütkepohl approach, a specific identification methodology for structural VAR, was employed in all models. This approach is a form of identification procedure as delineated by Lanne & Lütkepohl (2008).

7. Conclusion and Suggestions

This study examines the identification of stock price shocks as an instrument of unconventional monetary policy using a structural vector autoregressive model with applied heteroscedasticity identification. The endogenous variables considered were inflation, unemployment, stock prices, interest rates, GDP, and two regimes. The findings indicated that variability in stock prices enables the estimation of pertinent parameters. Consequently, the model was examined by employing several matrices on stock prices and additional variables to identify unconventional monetary policy. Stockholders realize profit or loss based on the disparity in stock prices at the time of acquisition and selling, influenced by numerous factors on the company's stock value, including stock liquidity, dividends, and free cash flow. Monetary policies are significant external environmental elements influencing the stock market; when executed effectively, they impact stock prices and can lead to an increase in stock valuations and economic prosperity. The findings indicated that stock prices in Colombia, Indonesia, Iran, Russia, and Saudi Arabia constitute an effective monetary policy that contributes to GDP growth. Consequently, unconventional monetary policy implemented by governments assists joint stock businesses in enhancing their liquidity and addressing financial challenges through the appreciation of stock values. The slope policies enacted by governments like Colombia, Iran, and Russia can facilitate economic recovery by decreasing unemployment and credit expenses. It should be noted that the Central Bank of Iran may utilize this strategy to enhance the conditions of its stock and securities market (financial markets). Implementing unconventional monetary policy can enhance the liquidity and dividends of the stock market. Furthermore, stock prices serve as a crucial instrument in this policy, facilitating output growth and mitigating inflation in Iran. Consequently, this approach may prove beneficial in alleviating the stagflation conditions and the volatility of the stock market in Iran as well as stimulating aggregate demand in the economy. An increase in stock prices can also reduce borrowing costs and boost investment.

Some limitations of the study are that 1) It is a fact that stock price changes are influenced by investor sentiment. A recent example of this is the recent negotiations between Iran and the United States of America and the sentiment of shareholders and the capital market due to optimistic expectations of these negotiations. However, quantifying these sentiments requires another study. It also should be noted that the scope of this article is far from the impact of shareholder sentiment on stock prices. 2) Stock prices may also reflect non-monetary factors (e.g., oil price volatility, geopolitical risks), especially in fuel-exporting countries. Finally, future researchers could replicate the study by considering global oil prices, geopolitical risks as variables alongside other variables to provide a more granular understanding of UMP and its impact on these factors in addition to its impact on stock prices. 3) the exclusion of oil prices and global financial conditions from the SVARIH model could bias the results, and this is a limitation of the SVARIH approach used. Future researchers also can apply factor-augmented VAR, high-frequency identification as well as external instrument approaches for estimating these factors in monetary policy.

Author Contributions

Conceptualization, all authors; methodology, all authors; validation, all authors; formal analysis, all authors; resources, all authors; writing—original draft preparation, all authors; writing—review and editing, all authors; supervision, all authors. All authors have read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest.

Data Availability Statement

The data used in the study were taken from https://data.worldbank.org/

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Appendix 1:

Prior to estimating the model, it is essential to assess the stationary. In addition to the Augmented Dickey-Fuller unit root test, the DF-GLS unit root test was used, which is a strong test for small samples. DF-GLS unit root test is conducted for all models. Table 1-1 presents the DF-GLS unit root tests of the variables.

Table 1.1. Results of DF-GLS unit root test

	Indonesia			Colombia	
critical value	DF-GLS mu	variables	critical value	DF-GLS mu	variables
-1.60	-1.83	$linf$	-1.95	-2.295	$linf$
-1.60	-2.093	$lunm$	-1.95	-2.211	$lunm$
-1.60	-2.365	lsp	-1.95	-1.98	lsp
-1.60	-2.124	lr	-1.95	-2.343	lr
-1.60	-2.289	$lgdp$	-1.60	-1.76	$lgdp$
	Russia			Iran	
-1.60	-3.171	$linf$	-1.60	-2.404	$linf$
-1.60	1.64	$lunm$	-1.60	-2.247	$lunm$
-1.60	-3.234	lsp	-1.60	-2.516	lsp
-1.60	-2.847	lr	-1.60	-1.647	lr
-1.60	2.121	$lgdp$	-1.60	1.819	$lgdp$
				Saudi Arabia	
			-1.60	-1.76	$linf$
			-1.60	-2.331	$lunm$
			-1.60	-2.87	lsp
			-1.60	-2.052	lr
			-1.60	-3.746	$lgdp$

Source: *research findings*

In addition to the DF-GLS unit root test, diagnostic tests, Normality and stability tests were summarized in tables below.

Table 1.2. Results of diagnostic tests, Normality and stability tests (Structural vector autoregressive with heteroskedasticity identification method) for Colombia

Second model		first model	
0.12	Probability in LM test	0.94	Probability in LM test
0.21	Normality probability	0.99	Normality probability
0.95	Eigenvalue modulus	0.81	Eigenvalue modulus
0.60		0.63	
0.50		0.53	
0.12		0.14	

Source: *research findings*

Table 1.3. Results of diagnostic tests, Normality and stability tests (Structural vector autoregressive with heteroskedasticity identification method) for Indonesia

Second model	first model

0.39	Probability in LM test	0.21	Probability in LM test
0.58	Normality probability	0.27	Normality probability
0.97		0.89	
0.86	Eigenvalue modulus	0.75	Eigenvalue modulus
0.64		0.53	
0.14		0.33	

Source: *research findings*

Table 1.4. Results of diagnostic tests, Normality and stability tests (Structural vector autoregressive with heteroskedasticity identification method) for Iran

Second model		first model	
0.39	Probability in LM test	0.19	Probability in LM test
0.57	Normality probability	0.41	Normality probability
0.90		0.94	
0.64	Eigenvalue modulus	0.67	Eigenvalue modulus
0.35		0.59	
0.23		0.27	

Source: *research findings*

Table 1.5. Results of diagnostic tests, Normality and stability tests (Structural vector autoregressive with heteroskedasticity identification method) for Russia

Second model		first model	
0.52	Probability in LM test	0.90	Probability in LM test
0.44	Normality probability	0.25	Normality probability
0.83		0.77	
0.62	Eigenvalue modulus	0.64	Eigenvalue modulus
0.072		0.56	
0.021		0.44	

Source: *research findings*

Table 1.6. Results of diagnostic tests, Normality and stability tests (Structural vector autoregressive with heteroskedasticity identification method) for Saudi Arabia

Second model		first model	
0.87	Probability in LM test	0.24	Probability in LM test
0.31	Normality probability	0.60	Normality probability
0.97		0.98	
0.72	Eigenvalue modulus	0.52	Eigenvalue modulus
0.43		0.17	
0.17		0.17	

Source: *research findings*

In Tables 1-2 to 1-6 (probability in LM test), Since p-values are larger than 0.05, which means there’s no significant autocorrelation in residuals. This is good for our model validity. Normality probabilities also show that all p-values are larger than 0.05 and the null hypothesis of normality is not rejected. That means residuals do not significantly deviate from normal distribution which is a good sign for models validity. All eigenvalue’s moduli are less than 1 illustrating that all lie inside the unit circle and our models are stable.

Table 1.7. Results of Multicollinearity tests for Colombia

Second model		first model	
variables	VIF	variables	VIF
lsp	1.96	lr	1.36
lunm	1.96	lsp	1.36

Source: *research findings*

Table 1.8. Results of Multicollinearity tests for Indonesia

Second model		first model	
variables	VIF	variables	VIF
lsp	1.78	lr	3.07
lunm	1.78	lsp	3.07

Source: *research findings*

Table 1.9. Results of Multicollinearity tests for Iran

Second model		first model	
variables	VIF	variables	VIF
lsp	1.29	lr	2.48
lunm	1.29	lsp	2.48

Source: *research findings*

Table 1.10. Results of Multicollinearity tests for Russia

Second model		first model	
variables	VIF	variables	VIF
lsp	1.03	lr	1.00
lunm	1.03	lsp	1.00

Source: *research findings*

Table 1.11. Results of Multicollinearity tests for Saudi Arabia

Second model		first model	
variables	VIF	variables	VIF
lsp	1.40	lr	1.00
lunm	1.40	lsp	1.00

Source: *research findings*

To assess the presence of multicollinearity among the explanatory variables, we conducted a Variance Inflation Factor (VIF) analysis. The results in Tables 1-7 to 1-11 show that all VIF values are well below the commonly used threshold of 10, we conclude that multicollinearity is not a concern in the models.