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Dynamic Relationship between the Return of Gold, Crude Oil, and the Stock Exchange of Thailand Based on a Vector Autoregressive Model

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ABSTRACT

This research aims to investigate the dynamic relationship between the return of gold (RGOLD), crude oil (RCO), and the stock exchange of Thailand (RSET) using the Vector Autoregressive model: VAR(p) to analyze the secondary monthly data from January 2002 to October 2021. The paper reports three key findings. Firstly, the Granger causality test reveals two direct relationships: one between RCO and RSET, and the other between RSET, RCO, and RGOLD. Moreover, the researcher estimated the relationship between these variables by using the VAR(1) model. Secondly, the impulse response function (IRF) is applied by Granger causality results. When a variable is shocked by an impulse in the system, the RCO to RSET response increases by 0.21%, the RSET to RGOLD response increases by 0.10%, and the RCO to RGOLD response increases by 0.04%, before decreasing and approaching equilibrium. Finally, variance decomposition shows that the greatest portion of total variation in RGOLD, RCO, and RSET can be explained by itself in the long run. Moreover, the variation of RSET can be affected by the variation of RCO while the variation of RGOLD can be affected by the variation of RCO and RSET. Thus, investors, securities analysts, or fund managers can use the study's results for strategic investment planning.

Keywords: Gold, Crude oil, Stock exchange of Thailand, Vector autoregressive
JEL Classifications: C22, E44

1. INTRODUCTION

Investors possess different levels of expertise, interests, specialties, and financial capacity. Although each investor may make investment decisions based on individual's aptitude and risk appetite, all investors expect some level of return on their investment. Nowadays, investors can explore investment opportunities in a wide range of assets. This study focuses on three major investment assets – gold, crude oil, and financial asset – that are fundamental to the economy. Gold has long been regarded as a safe-haven asset (Raza et al., 2016; Gao et al., 2020). Besides, gold can be used as an inflation hedge, a medium of exchange (Baur and Lucey, 2010), and is currently one of the international reserves. Crude oil is a popular alternative investment asset as it is a necessary energy source so critical for industrial manufacturing which impacts the economy at large. Lastly, investing in financial assets in stock markets is appealing due to high liquidity, regulatory oversight, and a standardized exchange system. Furthermore, some investors may seek greater return in the emerging financial markets.

The stock exchange of Thailand (SET) has attracted domestic and foreign investors as one of the emerging markets, with its average 20-year total return of approximately 18% per year. Since these investment assets have unique and diverse characteristics, including rate of return and risk, investors must understand and analyze their distinctive traits to maximize the investment portfolio and its potential return.

Currently, the new era of communication technology has integrated all information, including financial and economic data (e.g., financial reports, macroeconomic data, international news, etc.). Thus, it creates unprecedented investment opportunities and in turn affects price movements (Nairobi et al., 2022).

Price fluctuations in one market can rapidly propagate other markets. In recent decades, there has been much research effort to study the relationship between gold, crude oil, and the stock markets (Jain and Biswal, 2016; Coronado et al., 2018; Tursoy and Faisal, 2018; Shabbir and Kousar, 2020; Shaikh, 2021), and discover evidence from developed or emerging markets yielding various results. (Samanta and Zadeh, 2012; Partalidou et al., 2016; Raza et al., 2016; Arfaoui and Rejeb, 2017; Wei and Guo, 2017; Pandey and Vipul, 2018; Alio et al., 2019; Singhal et al., 2019; Kumau et al., 2020). Some of the empirical studies employed vector autoregressive model (VAR) (Ding et al., 2016; Alio et al., 2019; Chkili, 2022; Grabias, 2022; Nairobi et al., 2022). However, not a single study was able to explain the specific relationship between gold, crude oil, and the stock market.

Consequently, this research aims to study the dynamic relationship between gold, crude oil, and the stock exchange of Thailand (SET). The vector autoregressive model is chosen as a method because it is simple to estimate, can be calculated using the least squares method, and asymptotically equivalent to the maximum likelihood method (Tsay, 2014). Moreover, VAR is related to multivariate multiple regression which is very useful for explaining the dynamic relationship of time-series data. (Lutkepohl, 2009; Nairobi et al., 2022). Furthermore, we can apply the empirical VAR(p) results to the impulse response function and examine the variance decomposition among the variables. The investors, securities analysts, or fund managers can apply the study's result to their investment decision in gold, crude oil, or SET, and portfolio diversification while also consider important variables that may affect the investment portfolios during various economic crises in the future.

This research is structured as follows; Section 2: literature review; Section 3: data and methodology; Section 4: results and discussion; Section 5: conclusion.

2. LITERATURE REVIEW

Related literatures were reviewed to investigate the dynamic relationship and the Granger causality between gold, crude oil, and the stock markets. The recent empirical studies are explained as follows:

Singhal et al. (2019) studied the dynamic relationship between WTI crude oil prices, international gold prices, exchange rate, and the stock market in Mexico. The results of the autoregressive distribution lag test (ARDL) indicated a positive relationship between the gold prices and the stock market, but a negative relationship between the oil prices and the stock market. In contrast, Chkili (2022) used standard VAR and Markov switching VAR models to investigate the linkages between gold, oil prices, and the Islamic stock market. The findings suggested a positive relationship between oil and the Islamic stock market, but a negative relationship between gold and the Islamic stock market. Grabias (2022) tested the influence between the WTI oil market and the US stock market (namely, S&P index) using unrestrained VAR. The findings showed that crude oil had a short-term impact on the stock market, but that the stock market had no impact on the oil market.

Alio et al. (2019) employed traditional VAR to analyze the relationship between energy prices, e.g., crude oil, natural gas, and liquefied NGS, on the Nigerian stock market. The finding of the study concluded that changes in the energy prices had insignificant impact on the stock market, implying that other macroeconomic indicators could be more responsive to the stock market.

Coronado et al. (2018) used linear and non-linear Granger causality tests to analyze the direction of the causality between crude oil, gold, and the stock market.The result showed that causality occured in all directions; the change in the return of crude oil and gold affected the change of the stock market return, and vice versa. Tursoy and Faisal (2018) explored long-term and short-term interactions between stock prices, gold prices, and crude oil prices in Turkey, using the ARDL model and the Granger causality test. Their findings revealed a negative relationship between gold and stock prices, but a positive relationship between crude oil and stock prices. Furthermore, the Granger causality showed a long-term and short-term relationship between gold prices and stock prices.

By using a structural vector autoregressive model, Ding et al. (2016) analyzed the contagion effect of international crude oil price fluctuations on the Chinese stock market investor sentiment. The findings showed that the crude oil prices do Granger causality to the stock market investor sentiment; thereby the crude oil prices had a negative effect on the stock market investor sentiment.

The impact of gold prices, oil prices, and the stock market was examined in many other empirical research. For example, the study by Shabbir and Kousar (2020) applied the ARDL revealed a long-term relationship between gold and oil prices on the stock market, but the short-term relationship was non-existent. Raza et al. (2016) used the nonlinear ARDL (NARDL) model to assess the asymmetric impact of gold prices and oil prices on the stock markets of emerging economy. The findings indicated that gold prices had a significant negative impact on the stock markets of Mexico, Malaysia, Thailand, Chile, and Indonesia. Also, oil prices impacted all emerging stock markets negatively. Meanwhile, the research by Kumar et al. (2021) studied an asymmetric causality among crude oil prices, gold prices, natural gas prices, exchange rate, and the stock market index in India by using the NARDL bound test. In the long run, the findings showed that gold prices positively and asymmetrically impacted crude oil prices. Morema and Bonga-Bonga (2020) examined the effect of oil and gold price fluctuations on the South African stock market. Their findings provided evidence to suggest that there was unidirectional volatility transmission from oil and gold to the South African stock market as well as a dynamic correlation between commodity prices and the stock market.

In Thailand, Sinlapates et al. (2021) examined the relationship and volatility spillover between the return of gold, oil, and the Thai stock market by applying the diagonal BEKK-GARCH model. The findings revealed a unidirectional and positive return spillover from oil return to stock return and a bidirectional return spillover from gold return to stock return.

The empirical research mentioned above found mixed relationships among commodity prices and stock markets. Nevertheless, the majority suggested that a statistically significant dynamic relationship, between gold, crude oil, and the stock markets which had impact on securities for diversification investment. Therefore, the current study investigates on these selected commodities, employing the VAR(p) model. Furthermore, unlike any of the previous studies which concerned the total return of the stock market and the dynamic response between commodities and the market. The current study instead considers the assets for practical investment by applying impulse response and variance decomposition. In addition, this study collects data for a longer period (20-year time-series data) to confirm any possible relationship, while factoring in various economic crises such as the great recession, the European crisis, and the COVID-19 pandemic.

3. DATA AND METHODOLOGY

3.1. Data

Data collected are monthly commodity prices from the economic research Federal Reserve Bank of St. Louis, the stock exchange of Thailand (SETSMART database), and the CEIC database from January 2002 to October 2021, a total of 238 observations. The observed items consist of gold 99.99%, WTI crude oil and the stock exchange of Thailand total return index the investment total return of common stock that includes capital gain/loss, right offering and dividend - Lastly, the prices and index are transformed into continuous compounding return, which is calculated by natural logarithm form as follows:

$$R_{i,t} = ln\left(\frac{Price_{i,t}}{Price_{i,t-1}}\right)\times 100 \tag{1}$$

where: $R_{i,t}$ is a continuous compounding return., $Price_{i,t}$, $Price_{i,t-1}$ are a variable price at time *t*, and *t-1*, respectively.

3.2. Econometric Methodology

This study applies the VAR(p) model to investigate the dynamic relationship between gold, WTI crude oil, and the total return of the stock exchange of Thailand. There are three steps: The first step is a Granger causality test, which examines independent variable that affect dependent variable, before using a VAR(p) model to estimate the relationship; the second step is an Impulse Response Function (IRF); the final step is the Variance Decomposition (VD), which is explained in detail as follows:

3.2.1. Variance autoregressive model

The Vector Autoregressive model (VAR) is one of the most common statistical models used for financial evidence research to explain the relationship between multiple variables that fluctuate over time. VAR is a useful tool to describe the dynamic behavior of economic and financial time series in which a dependent or endogenous variable is determined by its own lagged variable or lagged of other variables but can only be employed with stationary time-series data.

The VAR(p) model can be written as follows:

$$Y_t = A_0 + A_1Y_{t-1} + A_2Y_{t-2} + \ldots + A_pY_{t-p} + \varepsilon_t \tag{2}$$

Where: $Y_t = \begin{bmatrix} RSET_t \\ RGOLD_t \\ RWTI_t \end{bmatrix}_{3\times1}$, $A_0 = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \\ \alpha_{30} \end{bmatrix}_{3\times1}$,

$A_i = \begin{bmatrix} \alpha_{11,i} & \alpha_{12,i} & \alpha_{13,i} \\ \alpha_{21,i} & \alpha_{22,i} & \alpha_{23,i} \\ \alpha_{31,i} & \alpha_{32,i} & \alpha_{33,i} \end{bmatrix}_{3\times3}$, $i = 1,\ldots,p$ and $\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}_{3\times1}$

which is white noise disturbances with zero mean, and covariance matrix is $E\left[\varepsilon_t, \varepsilon_{t-i}^{'}\right] = \Sigma^{\varepsilon}; \varepsilon_t \sim i.i.d.(0, \Sigma^{\varepsilon})$.

More explicitly, the three-equation VAR(p) model represents as follows:

$$RSET_t = \alpha_{10} + \sum_{i=1}^{p}\alpha_{11,i}RSET_{t-i} + \sum_{i=1}^{p}\alpha_{12,i}RGOLD_{t-i} + \sum_{i=1}^{p}\alpha_{13,i}RCO_{t-i} + \varepsilon_{1t} \tag{3}$$

$$RGOLD_t = \alpha_{20} + \sum_{i=1}^{p}\alpha_{21,i}RSET_{t-i} + \sum_{i=1}^{p}\alpha_{22,i}RGOLD_{t-i} + \sum_{i=1}^{p}\alpha_{23,i}RCO_{t-i} + \varepsilon_{2t} \tag{4}$$

$$RCO_t = \alpha_{30} + \sum_{i=1}^{p}\alpha_{31,i}RSET_{t-i} + \sum_{i=1}^{p}\alpha_{32,i}RGOLD_{t-i} + \sum_{i=1}^{p}\alpha_{33,i}RCO_{t-i} + \varepsilon_{3t} \tag{5}$$

Where: RSET, RGOLD, and RCO represent the monthly compounding continuous returns of the stock exchange of Thailand total return, gold, and WTI crude oil, respectively. *p* is an optimal lag length.

During the first step, VAR(p) model is estimated. The stationary data by the unit root test and select optimal lags of the endogenous variable are examined. The most commonly used criteria include the Akaike information criterion (AIC), Schwarz information criterion (SIC), and Hannan-Quinn information criterion (HQ), all of which are selected by minimizing values to determine *p* in the VAR model. Ultimately, VAR is applied to three applications of summary analysis, shown in detail as follows:

3.2.2. Granger causality test

Granger (1969) is based on a bivariate VAR(p) model to test whether the past and current value of *X* can be conducive to predicting the future value of *Y*. In other words, the direction of causality between *X* variable and *Y* variable is derived from a hypothesis as shown below:

$$H_0 : \alpha_{i,1} = \alpha_{i,2} = \ldots = \alpha_{i,p} = 0$$

$$H_1 : \alpha_{i,1} \neq \alpha_{i,2} \neq \ldots \neq \alpha_{i,p} \neq 0$$

The null hypothesis cannot be rejected if and only if $R_{i,t}$ does not Granger cause $R_{j,t}$ (i.e., *i* and *j* are RSET, RCO, or RGOLD) but can be rejected if and only if $R_{i,t}$ does Granger cause $R_{j,t}$. Consequently, VAR(p) model can reliably forecast the time-series data.

3.2.3. Impulse response function

Impulse Response Function (IRF) analysis is another feature within the VAR(p) model to examine the dynamic response among variables over a period of time after a shock. When an endogenous variable is shocked by an impulse at time *t* and responds at time *t+i* $(i \geq 0)$, the IRF transforms VAR(p) model into Vector Moving Average (VMA [∞]), which is shown the general form in equation 6. Hence, the IRF results can be interpreted by a graph indicating the direction and the times of adjustment to equilibrium.

$$Y_t = \mu + \sum_{i=0}^{\infty} \varnothing_i \varepsilon_{t-i} \quad (6)$$

Where: μ is the constant term, $\varnothing_i$ is the coefficient matrix, ε_t is the error vector.

3.2.4. Variance decomposition

Variance Decomposition is used to determine the causal association between variables in a system over time (Sujit and Kumar, 2011). The method provides the proportion of variance in component shocks for investors, securities analysts or fund managers to focus on the important variable that is affected when the innovations (shocks) occur in the VAR model.

4. RESULTS AND DISCUSSION

4.1. Variance Autoregressive Model: VAR(p)

Table 1 Panel A presents descriptive statistics of return, with the average return (Mean) in the range of 0.53 (RCO) to 1.01 (RSET), while considering the volatility from standard deviation, which is in the range of 3.66 (RGOLD) to 10.77 (RCO). That means the crude oil return has the highest volatility of all. Additionally, the skewness of all variables is negative, and kurtosis has more than 3 (Leptokurtic), which indicates that the RCO and RSET are non-normal distributions, but the Jarque–Bera test confirms that RGOLD follows a normal distribution, i.e., the null hypothesis that the return of gold has a normal distribution for the significant level at 0.05 is accepted. In addition, Panel B shows the correlation between variables; RCO and RSET show the highest correlation (16.12%) while RCO and RGOLD show the lowest correlation (3.75%).

Table 2 provides the unit root test or stationary data using the Augmented Dickey-Fuller (ADF) (Dicky and Fuller, 1979) and Phillips-Perron (PP) techniques (Phillips and Perron, 1988). The result shows that all variables are stationary at level I(0), i.e., rejected null hypothesis that continuous compounding return has a unit root or non-stationary. Furthermore, the optimal lag by AIC, SIC, and HQ criteria are examined. Table 3 shows that there is 1 lag. Accordingly, this paper applies the VAR model at 1 lag, which is called the VAR(1) model. Therefore, we can apply the VAR(p) model to estimate the relationship between RCO, RGOLD, and RSET.

Moreover, the Granger causality test is determined, as demonstrated in Table 4. The results show that the null hypothesis that implies a direct relationship between RCO and RSET for a significant level at 0.01 can be rejected. Similarly, RCO and RSET have a direct influence on RGOLD for a significant level at 0.05. However, the null hypothesis of RGOLD to RSET, RSET to RCO, and RGOLD to RCO, which concludes that RGOLD does not Granger causes RSET, RSET and RGOLD do not Granger cause RCO, cannot be rejected.

By applying VAR(p) model as shown above, the researcher is able to estimate VAR(1), demonstrated in Table 5. VAR(1) does not only present the dynamic relationship between variables but also suggest that each variable's own lag can predict future return.

For residual diagnostic check, if all the inverse roots of the autoregressive characteristic polynomial are in the unit circle $(|Z| \leq 1)$, the model is deemed stable (stationary). The finding in Figure 1 shows the inverse roots within the unit circle. Therefore, we can implement the VAR(1) result and subsequently analyze the impulse response and variance decomposition analysis.

4.2. Impulse Response Function Analysis Base on VAR Model

The results of the impulse response function (IRF) that is applied from the Granger causality results can be described as follows.

The response of RSET to a shock of RCO (RCO→RSET) is a positive effect. When the return of WTI crude oil has a shock, increasing 1% at the present (t=0), the effect of RSET will increase

Table 1: Descriptive statistics of returns

Panel A: Descriptive Statistics			
	RCO	**RGOLD**	**RSET**
Mean	0.5251	0.7806	1.0120
Median	1.7980	0.6888	1.2006
Maximum	54.5621	11.6768	17.8790
Minimum	−56.8125	−11.9069	−35.8047
Std. Dev.	10.7712	3.6620	5.8700
Skewness	−1.0158	−0.0471	−1.0656
Kurtosis	11.1216	3.4079	9.2977
Jarque−Bera	695.0408	1.7377	438.3549
P-value	0.0000***	0.4194	0.0000***
Observations	238	238	238
Panel B: Correlation Matrix			
	RCO	**RGOLD**	**RSET**
RCO	1.0000		
RGOLD	0.0375	1.0000	
RSET	0.1612	0.1093	1.0000

***Represents the significant level at 0.01. Source: The author's calculation

Table 2: Unit root test

Variable	Augmented Dickey-Fuller (ADF)			Phillips-Perron (PP)		
	t-Stat	P-value	Order of Integration	t-Stat	P-value	Order of Integration
RCO	−11.4063***	0.0000	I (0)	−10.9040***	0.0000	I (0)
RGOLD	−12.4116***	0.0000	I (0)	−12.4386***	0.0000	I (0)
RSET	−13.0128***	0.0000	I (0)	−13.2386***	0.0000	I (0)

***Represents the significant level at 0.01. Source: The author's calculation

Table 3: Optimal lag order of Vector Autoregressive

Lag	AIC	SIC	HQ
0	19.4288	19.4742	19.4471
1	19.1591*	19.3407*	19.2324*
2	19.1695	19.4874	19.2978
3	19.1901	19.6442	19.3734

AIC, SIC, and HQ are used to determine the optimal lag. *Represents the lowest value of AIC, SIC, and HQ criterion

Table 4: Granger causality test using lag order from VAR (1)

Granger Causality Test (H0)	χ^2statistics	Prob.	Result		
RGOLD does not Granger cause RSET	0.2697	0.6036	RGOLD	↛	RSET
RCO does not Granger cause RSET	42.7055***	0.0000	RCO	→	RSET
RSET does not Granger cause RGOLD	6.2357**	0.0125	RSET	→	RGOLD
RCO does not Granger cause RGOLD	4.0161**	0.0451	RCO	→	RGOLD
RSET does not Granger cause RCO	0.0581	0.8095	RSET	↛	RCO
RGOLD does not Granger cause RCO	1.9308	0.1647	RGOLD	↛	RCO

The null hypothesis is that Ri does not Granger cause Rj (i.e., Ri↛Rj)., ***, **Represents the significant level at 0.01 and 0.05, respectively

Table 5: Estimated Coefficients using the VAR (1)

Panel C: Estimation Results			
Variable	RCO	RGOLD	RSET
Constant	0.1693	0.5305	0.7972
	[0.2433]	[2.2287]**	[2.2204]**
RCO	0.2856	0.0435	0.2140
	[4.5002]***	[2.0040]**	[6.5349]***
RGOLD	0.2570	0.1527	−0.0496
	[1.3890]	[2.4139]**	[−0.5193]
RSET	−0.0282	0.0998	0.0884
	[−0.2410]	[2.4971]**	[1.4673]
Adj. R-Squared	0.0776	0.0668	0.1636
F-Statistic	7.6158***	6.6273***	16.3842***

***, **Represent the significant level at 0.01, and 0.05, respectively. [] represents t-statistic. Source: The author's calculation

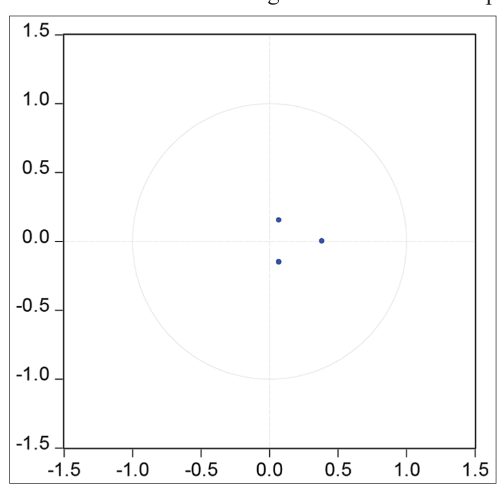
by 0.21% in the following month before declining steadily to equilibrium in the next 7 months. This result is similarly to the response of RGOLD to a shock of RSET (RSET→RGOLD) and RGOLD to RCO (RCO→RGOLD). When a shock occurs in the

Table 6: Forecast error variance decomposition

Panel D: Variance Decomposition of RSET				
Period	Standard Error	Variance Decomposition (Percent)		
		RCO	RGOLD	RSET
1	5.3462	0.00	0.00	100.00
4	5.8830	16.20	0.23	83.57
8	5.8839	16.22	0.23	83.55
12	5.8839	16.22	0.23	83.55
Panel E: Variance Decomposition of RGOLD				
Period	Standard Error	Variance Decomposition (Percent)		
		RCO	RGOLD	RSET
1	3.5445	0.00	99.86	0.14
4	3.6910	3.02	94.23	2.75
8	3.6918	3.05	94.20	2.75
12	3.6918	3.05	94.20	2.75
Panel F: Variance Decomposition of RCO				
Period	Standard Error	Variance Decomposition (Percent)		
		RCO	RGOLD	RSET
1	10.3626	99.66	0.06	0.28
4	10.8594	98.93	0.79	0.28
8	10.8605	98.93	0.79	0.28
12	10.8605	98.93	0.79	0.28

Source: The author's calculation

Figure 1: The inverse roots of autoregressive characteristic polynomial

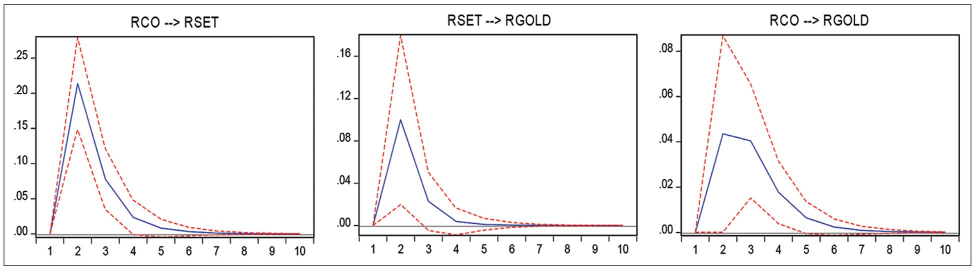


system, the return of gold will increase by 0.10 and 0.04% in the following month before declining and adjusting to equilibrium in the next 5 months and 8 months, respectively (Figure 2).

4.3. Variance Decomposition

The Variance Decomposition analysis, as demonstrated in Table 6, separates the variance proportion of returns from the VAR(1) model by itself (endogenous) or is determined by other variables in the system. Findings shown in Table 6 Panel D indicates that the variation of RSET can be affected by itself by 100% in the first

Figure 2: Impulse response of VAR(1) model



month. Later, its effect declines by an average of 87.67%. Also, in the long run, the variation of RSET can be determined by the variation of RCO by an average of 12.16%, but the variation of RSET is hardly affected by the variation of RGOLD. Additionally, Panel E indicates that in the first month, the variation of RGOLD can be affected by itself at 99.86% and that effect will dwindle by an average of 95.62%. In the long run, the variation of RCO and RSET determined the variation of RGOLD by an average of 2.28 and 2.10%, respectively. On the other hand, Panel F shows that the variation of RCO can be determined by itself by an average of 99.11%, which could imply that the variation of RSET and RGOLD barely explain the variation of RCO. Accordingly, the finding of variance decomposition is confirmed to be consistent with the Granger causality result.

5. CONCLUSION

This paper examines the dynamic relationship between the return of gold (RGOLD), crude oil (RCO), and the stock exchange of Thailand (RSET) using the VAR(1) model. The empirical results show that RCO is positively correlated with RSET, highly responsive when the shock occurs, and will approach equilibrium in the long run. Otherwise, RSET is not affected by RGOLD. Furthermore, RCO and RSET have a positive correlation with RGOLD. When the impulse occurs in the system, both will increase then decrease to equilibrium in the long run. On the contrary, there are no significant factors in the model that respond to RCO. The study also examines the variance decomposition to identify the importance of each factor and its effects on the VAR(1). Findings: the variation of RCO is the largest portion of all variables, which explains the variation of RSET. Besides, the variation of RCO can be determined by RGOLD more than the variation of RSET. Conversely, the variation of RCO can be explained by itself or maybe by other economic factors. In conclusion, retail investors, institutional investors, securities analysts, or fund managers can use the study's results for strategic investment planning, including the diversification of securities investment or implementation during economic crises.

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