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Spillover Effects between Oil, Gold, Stock, and Exchange Rate Returns in Thailand: An Extended Joint Connected TVP-VAR Approach

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ABSTRACT

The objective of this study is to analyze the spillover effects among the returns of oil, gold, the stock market, and exchange rates in Thailand. Using the time-varying parameter vector autoregression model (TVP-VAR) with extended joint connectedness and data from April 2002 to March 2024, our analysis reveals a moderate level of the dynamic linkage among these returns. We observe that the dynamic connectedness among all returns varies over time, influenced by global economic events and country situations. Notably, in Thailand's landscape, stock market and gold returns act as net shock transmitters, with the stock market exhibiting the highest volatility among all variables, while oil and exchange rate markets function as net recipients. These insights significantly contribute to understanding asset and commodity markets and offer valuable policy implications for effectively managing these markets.

Keywords: Extended Time-Varying Parameter Vector Autoregression, Spillover Effects, Oil, Gold, Stock Market, Exchange Rate
JEL Classification: A1

1. INTRODUCTION

Understanding the interplay between financial and commodity markets is crucial for economists and policymakers due to potential contagion effects following shocks in one market. For example, the East Asian crisis in 1997 highlighted significant cross-country correlations among currencies and sovereign spreads in Indonesia, Korea, Malaysia, the Philippines, and Thailand (Baig and Goldfajn, 1998). Since the 1970s, with crude oil pricing denominated in US dollars, the interaction between crude oil, stock markets, and foreign exchange markets has become prominent (Golub, 1983; Krugman, 1983; Basher et al., 2016). The increasing complexity of financial instruments and market expansion underscores the need for theoretical and empirical understanding of market interconnectedness. Given global economic volatility and geopolitical uncertainty, studying spillover effects across asset classes has become especially important.

Given the dynamic nature of participants in gold, oil, stock, and exchange rate markets, which exhibit diverse traits influenced by factors like risk preferences, investment goals, sentiment, and economic outlook, recognizing the interconnectedness among these markets is crucial for understanding financial dynamics and broader economic implications. Consequently, various studies have explored the relationships between these markets. Numerous studies have investigated the relationship between oil and gold markets, with some conducted prior to COVID-19 (Narayan et al., 2010; Zhang and Wei, 2010; Antonakakis and Kizys, 2015; Sephton and Mann, 2018; Bedoui et al., 2019) and others after the pandemic (Tanin et al., 2021; Gharib et al., 2021; Huang and Wu, 2021; Selvanathan and Selvanathan, 2022; Huseynli, 2023). Similarly, many studies have examined the relationship between oil and stock prices (Kilian and Park, 2009; Sardar and Shamar, 2022; Magazzino et al., 2023). The dynamic relationship between oil prices and macroeconomic variables, including exchange rates, has also received significant attention in the literature. Therefore, the relationship between oil prices and exchange rates has been widely examined (Harnphattananusorn, 2022; Aloui et al., 2011, 2013; Reboredo et al., 2014; Bal and Rath, 2015; Basher et al., 2016; Hussain et al., 2017; Yang et al., 2017; Ji et al., 2019; Beckmann et al., 2020). Crude oil, gold, and stock markets are closely interlinked; most financial market research has found a dependence or risk contagion between these markets (Negi et al., 2011; Shabbir, 2020; Marwanti and Robiyanto, 2021; Nguyen et al., 2023). Moreover, the stock market's response to movements in oil prices, gold prices, and exchange rates has been studied, yielding inconsistent and ambiguous findings (Asaad, 2014). Some studies have investigated the relationship between oil, gold, stocks, and exchange rates, as seen in (Sujit and Rajesh Kumar, 2011; Ingalhalli et al., 2016; Lubis et al., 2021; Asaad, 2021; Huang et al., 2023).

Estimation techniques of literatures above include both static with system of linear relationships using cointegration tests,VAR, VECM, and ARDL models (Sadorsky, 1999; Kilian and Park, 2009; Negi et al., 2011; Shabbir, 2020; Asaad, 2021; Cui et al., 2022), as well as non-linear relation among variables of interest using NARDL (Harnphattananusorn, 2022; Cui et al., 2022). Additionally, the dynamic or time invariant relationship have been explored the relationship using VAR-DCC-GARCH, TVP-VAR models (Hashmi et al., 2022; Huang et al., 2023; Nguyen et al., 2023; Lu et al., 2023; Manuel et al., 2024).

Several researchers have observed structural changes over time in the macroeconomy. Sims and Zha (2006) discovered variations in the variance of exogenous shocks, while Primiceri (2005) and Koop et al. (2009) noted that the connections among variables have also evolved over time. Therefore, static models may fail to capture the true nature of relationships among variables. This limitation highlights the need for more flexible modeling approaches that can adapt to changing economic conditions. The Time-Varying Parameter Vector Autoregression (TVP-VAR) model offers a solution by allowing parameters to vary over time, thereby capturing the evolving nature of economic relationships.

Thailand has experienced fluctuations and interdependencies similar to those observed in global financial markets. Its integration into the global economy, along with domestic economic reforms and evolving political landscapes, has rendered macroeconomic variables such as exchange rates and stock market returns vulnerable to external influences such as oil and gold prices. Understanding these dynamics comprehensively is crucial. Therefore, this paper aims to explore spillover effects within Thailand's financial markets. To address the dynamic relationship, the study employs the time-varying parameter vector autoregression model (TVP-VAR), which enables the estimation of parameters that vary over time. Furthermore, the estimation results are not sensitive to outliers, thereby allowing researchers to capture dynamic relationships more effectively.

The paper is structured as follows. Section 2 presents a literature analysis of studies on the relationship between oil, gold stocks, and exchange rates. Section 3 includes data and the time-varying parameter VAR (TVP-VAR) model. Section 4 offers empirical findings on the dynamics of oil, gold, stock and exchange rate returns. Section 5 is conclusion and recommendation.

2. LITERATURES REVIEW

In recent years, there has been significant scholarly interest in exploring the dynamic relationships among oil prices, gold prices, exchange rates, and stock returns. Numerous studies have investigated the interconnectedness and spillover effects among these key financial and commodity markets. In this part, we group literatures by the relationship between (1) oil and other assets (gold, stock, and exchange rate), (2) oil, gold, and stock, and (3) oil, gold, stock, and exchange rate.

2.1. Oil and Gold

There is a large literature on the price relationship between gold and oil. Some of these studies are outlined below.

Zhang et al. (2010) analyzes the cointegration relationship and causality between gold and crude oil prices. The study finds that there are consistent trends between the crude oil price and gold price with significant positive correlation during the sampling period. The study further suggests that long term equilibrium between the two markets and the crude oil price change linearly Granger causes the volatility of gold price. With respect to the common effective price between the two markets, the contribution of the crude oil price seems larger than that of gold price.

Sephton and Mann (2018) use data from January 2, 2009, to May 26, 2017, and a linear cointegration test was utilized to analyze the US dollar Brent crude oil price and the closing US dollar London gold price. The results suggest that crude oil and gold prices exhibit cointegration within a non-linear framework, specifically within a non-traditional band-TAR framework. The study reveals a long-term relationship between crude oil and gold prices.

Huang and Wu (2021) discovered significant insights during the period of the COVID-19 outbreak, spanning from June 2018 to June 2021. Notably, it was observed that only oil market volatility demonstrated a unilateral impact. Volatility within the gold market, however, did not exhibit a substantial influence on the oil market.

Huseynli (2023) investigate the causal relationship between world oil prices and gold prices. The study is divided into two groups and evaluated as pre-pandemic and post-pandemic using daily data. According to the ADF Johansen cointegration and VAR results obtained by applying the first-order difference operation, it was concluded that there is a one-way causality relationship from gold prices to oil prices, before the pandemic.

2.2. Oil and Stock

Kilian and Park (2009) developed a VAR model using global oil production, a real economic activity index, oil prices considered as the costs paid by US refiners, and the CRSP equally weighted portfolio for US stock returns during 1973-2006. Empirical findings show that the reaction of the US real stock returns to a shock to the oil prices can differ heavily depending on whether the change in this price is caused by the demand or the supply in the relevant market. Both types of shocks accounted for almost 22% of the long-run variation in the US real stock returns.

Arouri and Rault (2012) used a multivariate GARCH model to analyze the interplay between stock market returns and oil prices in Gulf Cooperation Council (GCC) countries. They explored the interlinkages between oil prices and stock returns, emphasizing the importance of oil as a determinant of stock market movements due to its impact on production costs and consumer spending. The results showed that oil prices significantly affect stock market returns in the GCC countries, with varying magnitudes across different sectors.

Hashmi et al. (2022) investigates the impact of crude oil prices on the Chinese stock market and selected industries by using the VAR-DCC-GARCH model over the period from December 26, 2001, to April 30, 2019. The impact of Brent crude oil prices on the Shanghai Composite Index and selected industries is significant, with variations observed across different sample periods. Abrupt changes in oil prices increase the risk of spillover impacts on stock markets. Overall, Brent crude oil prices positively affect the Chinese stock market.

Sardar and Sharma (2022) investigated the nonlinear relationship between oil prices and the US stock returns around the zero lower bound (ZLB) between October 1987 and March 2020. Using state-dependent local projections, they find that oil price shocks cause an increase in stock returns when the economy is operating in the zero lower bound. On the other hand, oil prices and stock returns mostly show a negative relationship when interest rates are higher. Oil prices and stock returns exhibit a negative relationship during non-ZLB periods. Measures of economic activity also exhibit an asymmetric response to oil prices. Robust results are obtained using alternative measures of oil price shocks.

Magazzino et al. (2023) presents an in-depth analysis of the relationship between oil prices and European stock returns by using the time-varying Granger causality test and the structural vector auto-regression model. The empirical strategy implied an SVAR model and TVGC analyses, using monthly observations from 2007 to 2022 for both non-European and European oil production variations, the real economic activity index, Brent prices, and the Euro Stoxx 50 Index returns. One of the key findings of this study is that there exists a causal link from oil prices to the European stock returns. Furthermore, Brent prices seem to be caused by market returns.

2.3. Oil and Exchange Rate

Beckmann et al. (2020) examine the relationship between oil prices and exchange rates. They show identify strong links between exchange rates and oil prices over the long-run. Exchange rates and oil prices are useful predictors for each other in the short-run. The effects are strongly time-varying. Yet there are some common patterns: (i) strong links between exchange rates and oil prices are frequently observed over the long-run; and (ii) either exchange rates or oil prices are a potentially useful predictor of the other variable in the short-run, but the effects are strongly time-varying. Harnphattananusorn (2022) investigates the asymmetric relationship between exchange rate volatility and oil prices using a nonlinear autoregressive distributed lag (NARDL) model. To calculate exchange rate volatility, the GARCH (1,1) model is used. Monthly data from January 2000 through June 2021 are utilized. The findings reveal that oil price shocks have asymmetric impacts on Thailand's exchange rate volatility in both the long and short run.

Lu et al. (2023) investigate the relationship between crude oil futures and exchange rates. Through the utilization of a TVP-VAR (time-varying parameter VAR) extended joint connectedness methodology and the generalized connectedness technique to investigate the interconnectivity of oil futures prices of key oil-dependent nations and exchange rates, we contribute to the existing body of knowledge. The results indicate a time-varying nature of overall and pairwise connections, which typically intensifies during various periods such as the COVID-19 pandemic, Brexit, and the European sovereign debt crisis. The Japanese Yen and Russian Ruble appear as the primary recipients of net shocks, as suggested by both the generalized and joint connectedness methodologies. For other nations, similar methods yield conflicting results. Furthermore, there is clear evidence of time-dependent and bidirectional shock transmissions between the oil and foreign exchange markets.

2.4. Oil, Gold, and Stock

Negi et al. (2011) investigated the cointegration of oil prices and stock prices in India and China. The study used the Johansen Co-integration model to identify cointegration among these variables. The Vector Error Correction Model (VECM) was then used to evaluate the possibility of a long-run relationship between the variables. The results of the cointegration research revealed a long-run relationship between oil prices and stock market prices in India and China. This shows a significant and long-term relationship between these variables.

Raza et al. (2016) examined the asymmetric impact of gold prices, oil prices, and their associated volatilities on the stock markets of emerging economies, utilizing monthly data spanning from January 2008 to June 2015. Empirical results using the nonlinear autoregressive distributed lag (ARDL) approach showed complex effects: Large emerging economies like Brazil, Russia, India, and China (BRIC) as well as the stock markets of Mexico, Malaysia, Thailand, Chile, and Indonesia were all negatively impacted by rising gold prices. Additionally, Oil prices harm the stock markets of all emerging economies. Gold and oil volatilities have a negative impact on stock markets of all emerging economies in both the short- and the long-run. The results indicated that the stock markets in the emerging economies are more vulnerable to bad news and events that result in uncertain economic conditions.

Shabbir et al. (2020) find out the impact of gold and oil prices on the stock market in Pakistan, the data spanning from 1985 to 2016 was utilized, focusing on three key variables: Gold price, oil price, and stock market performance. The study employed the Autoregressive Distributed Lag (ARDL) approach to delineate the relationships between these variables. The analysis revealed a noteworthy positive and significant relationship between oil prices and the stock market. Additionally, it was observed that there exists a positive and significant correlation between gold prices and the stock market.

Marwanti and Robiyanto (2021) investigated the impact of oil and gold price volatility on stock returns in Indonesia with a focus on the periods before and during the COVID-19 pandemic. The findings of the study revealed that the volatility in oil and gold prices did not have a significant effect on stock returns during both periods.

Cui et al. (2022) estimate the dynamic relationship between oil prices, gold prices, oil prices volatilities and gold prices volatilities on the stock market of China. Using daily data over the period from 2009 to 2021, the study applied Autoregressive Distributed Lag (ARDL) bound test approach for the purpose of empirical estimation. Moreover, nonlinear ARDL and asymmetric causality analysis have also been applied for a more comprehensive understanding of asymmetry. The ARDL bound test indicates that gold prices and oil prices negatively affect the stock market.

Nguyen et al. (2023) analyzes the spillovers of oil prices, gold prices and stock market returns in Vietnam by using the time-varying parameter vector autoregression model (TVP-VAR). The results show a moderate interdependence among the variables from 2010 to 2022. Overall, stock market returns are net shock transmitters with the highest volatility among all the variables, while the oil and gold markets are net recipients. Furthermore, the spillover tends to increase in times of turmoil, geopolitical instability, and unfavorable natural conditions; for instance, in 2010-2012, 2017, and 2020.

2.5. Oil, Gold, Stock, and Exchange rate

Sujit and Rajesh Kumar (2011) investigated the dynamic relationship among gold price, stock returns, exchange rate, and oil price. The study analyzed daily data from January 2nd, 1998, to June 5th, 2011, employing time series techniques including VAR and cointegration methods to capture dynamic and stable relationships among these variables. Findings indicate that changes in other variables notably influence exchange rates. Furthermore, the study suggests a weak long-term relationship among the variables.

Ingalhalli et al. (2016) study on dynamic relationship between oil, gold, forex and stock markets in Indian context. To study the causal relationship between the oil, gold, forex, and stock markets using data ranging from January 2005 to July 2015, they employs the Granger causality test. The results indicate that the existence of only unidirectional relationship among the variables. The Granger causality test reveals that oil prices contribute towards development and forecasting of exchange rate and gold prices, whereas fluctuations in oil prices are granger caused by Sensex.

Lubis et al. (2021) examined changes in crude oil prices, gold prices and exchange rates on the basis of the Jakarta Composite Stock Price Index (JCI) during the COVID-19 pandemic from March 2020 to March 2021 using the ARCH/GARCH method. They found that there was no significant effect between the price of Crude Oil on the JCI, while gold price has a significant positive effect on JCI and exchange rate.

Asaad (2021) used the econometrics methods to identify the interactions among oil price, gold price, exchange rate, and stock price which represented by the (ISX60) index under the Iraq stock exchange pre-during global pandemic of COVID19. The study used the correlation matrix, unit root test to assure the stationary for the ARDL model and the granger causality test. The results indicated that there is no cointegration between the variables for the full sample period, both pre-during and pre-COVID19. For the during-COVID19 period, no decision could be made regarding the long-run relationship among the variables. Meanwhile, the short-run causal model results showed that the effects of oil price, gold price, and exchange rate were insignificant with the Iraq stock exchange.

Huang et al. (2023) investigates the dynamic volatility spillover among energy commodities and financial markets in pre-and mid-COVID-19 periods by utilizing a novel TVP-VAR frequency connectedness approach and the QMLE-based realized volatility data. They indicate that the volatility spillover is mainly driven by long-term components and prominently time-varying with a remarkable but short-lived surge during the COVID-19 outbreak. Additionally, they suggesting the energy commodity market becoming more integrated with, more influential and meanwhile vulnerable to global financial markets.

The literature review above investigates the complex linkages between oil, gold, stock, and exchange rate markets, both before and after the COVID-19 epidemic. It reveals deep connections between these variables through a thorough examination of both linear and nonlinear dynamics. The review illustrates the relationships between oil and gold, oil and exchange rate, oil and stock, as well as the combined dynamics of all these markets (oil, gold, stock, and exchange rate). These findings emphasize the interdependence of these commodities and financial assets during the chosen time period.

3. DATA AND METHODOLOGY

3.1. Data

The paper includes data on the crude oil price index, gold price, Thailand stock price index, and Thai Baht exchange rate. We gathered monthly data from CEIC and the Bank of Thailand, comprising the benchmark crude oil price index, gold price (in US Dollars per Troy Ounce), the SET index, and the Thai Baht exchange rate (BAHT/USD). The data spans from April 2002 to January 2024.

3.2. Methodology

This study examines the interconnectedness of oil, gold, stock, and exchange rate returns using Balcilar et al. (2021)'s TVP-VAR extended joint connectedness technique. This technique combines Antonakakis et al. (2020)'s TVP-VAR connectedness approach with the joint spillover approach of Lastrapes and Wiesen (2021), and we employed the estimation package developed by Gabauer (2022). This combination offers several advantages: (i) it eliminates the need for choosing an arbitrary window size,

(ii) no observations are lost, (iii) the estimation results are not outliers sensitive, (iv) it adapts to coefficients vary over time and (v) variance and co-variances are vary over time to better monitor the volatility. The method permits the capturing of spillovers not just between the returns of individual commodities, but also the cross-market spillovers among returns.

To estimate the dynamic interconnectedness based on the TVP-VAR(p) model, we use the following vector of endogenous variables: $y_t^{/} = \left[oil_t\, gold_t\, set_t\, ex_t\right]$ and TVP-VAR can be shown as following

$$y_t = \Phi_{1t} y_{t-1} + \Phi_{2t} y_{t-2} + \& + \Phi_{pt} y_{t-p} + \in_t \tag{1}$$

Where $\in_t \sim N(0, \Sigma_t)$ and $vec(\Phi_t) = vec(\Phi_{t-1}) + u_t, u_t \sim N(0, R_t)$. The vector y_t and $\in_t$ are $N \times 1$ vectors of variables and error term, Σ_t is the $N \times N$ time-varying variance-covariance matrix of error term, and Φ is the $N \times N$ dimensional matrix.

The TVP-VAR is transformed to a TVP-VMA model according to the Wold representation theorem as $y_t = \sum_{h=0}^{\infty} B_{h,t} \in_{t-i}$ where $B_0 = I_N$ and $\in$ is a vector of white noise shocks with (symmetric but not orthogonal) with $N\times N$ time-varying covariance matrix $E\left(\in_t \in_t^{'}\right) = \sum_t$. Thus, the H-step forecast error can be written as:

$$\psi_t(H) = y_{t+H} - E(y_{t+H} \mid y_t, y_{t-1}, \ldots) = \sum_{h=0}^{H-1} \mathrm{B}_{h,t} \in_{t+H-h}, \tag{2}$$

with a forecast error covariance matrix equal to: $E\left(\Psi_t(H)\Psi_t^{'}(H)\right) = B_{h,t}\, \Sigma_t\, B_{h,t}^{'}$.

For the original connectedness approach we have decided to employ the generalized connectedness approach (Diebold and Yılmaz, 2012; Diebold and Yılmaz, 2014; Wiesen et al., 2018) points out that this approach should be selected in case no proper economic theory is available. The H-step ahead generalized forecast error variance decomposition (GFEVD) introduced by Koop et al. (1996) and Pesaran and Shin (1998). The (scaled) GFEVD, $Spill_{ij,t}$, can be interpreted as the effect a shock in variable j has on variable i and can be formulated as follow.

$$\zeta_{ij,t}(H) = \frac{E\left(\Psi_{i,t}^2(H)\right) - E[\Psi_{i,t}(H) - E\left(\Psi_{i,t}(H)\right) | \in_{j,t+1}, \ldots, \in_{j,t+H}]^2}{E\left(\Psi_{it}^2(H)\right)} = \frac{\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i^{'} \mathrm{B}_{ht}\, \Sigma_t\, \boldsymbol{e}_j\right)^2}{\left(\boldsymbol{e}_j^{'}\, \Sigma_t\, \boldsymbol{e}_j\right) \sum_{h=0}^{H-1}\left(\boldsymbol{e}_i^{'} \mathrm{B}_{ht}\, \Sigma_t\, \mathrm{B}_{ht}^{'} \boldsymbol{e}_i\right)} \tag{3}$$

$$Spill_{ij,t} = \frac{\zeta_{ij,t}(H)}{\sum_{j=1}^{N} \zeta_{ij,t}(H)} \tag{4}$$

Where e_i is a $N\times 1$ zero selection vector with unity on its i th position and $\zeta_{ij,t}(H)$ the proportional reduction of the H-step forecast error variance of variable i due to *conditioning on the future shocks of variable j*. As $\sum_{j=1}^{N} \zeta_{ij,t}(H) \neq 1$, then it is normalized to unity by the row sum resulting in the generalized spillover table, $Spill_{ij,t}$.

Eqs. (3) and (4) facilitate the computation of all connectedness measures such as the total directional connectedness from others to variable i ($C_{i\rightarrow",t}^{to}$)and the total directional connectedness to others from a shock in variable i ($C_{i\leftarrow",t}^{from}$) which illustrate by how much the network influences variable i and how much variable i influences the whole network, respectively. This metrics can be written as:

$$C_{i\leftarrow",t}^{from} = \sum_{j=1, i\neq j}^{N} Spill_{ij,t} \tag{5}$$

$$C_{i\rightarrow",t}^{to} = \sum_{j=1, i\neq j}^{N} Spill_{ji,t} \tag{6}$$

The net total directional connectedness of variable i ($NET_{i,t}$) which demonstrates whether variable i influences the network more than being influenced by it:

$$NET_{i,t} = C_{i\rightarrow",t}^{to} - C_{i\leftarrow",t}^{from} \tag{7}$$

It represents the difference between the total directional connectedness TO others ($C_{i\rightarrow",t}^{to}$) and the total directional connectedness FROM others ($C_{i\leftarrow",t}^{from}$) which can be interpreted as the net influence variable i has on the corresponding volatility transmission network. If $NET_{i,t} > 0$ ($NET_{i,t} < 0$), variable i is a net transmitter (receiver) of shocks meaning that variable i influences all others j more (less) than being influenced by them.

The core of the connectedness center is the total connectedness index (TCI) that demonstrates the network interconnectedness which show the average impact a shock in one variable has on all others. The TCI is defined as the average total directional connectedness from (to) others and is formulated by the following

$$TSpill_t = \frac{1}{N}\sum_{i=1}^{N} C_{i\leftarrow",t}^{from} = \frac{1}{N}\sum_{i=1}^{N} C_{i\rightarrow",t}^{to}, \tag{8}$$

Note that a high value indicates a high degree of network spillovers

Finally, on a more disaggregated level, the connectedness approach provides information about the bilateral interrelationships of two variables by the concept of net pairwise directional spillovers (NPS) which are defined by:

$$NPS_{ij,t} = Spill_{ji,t}^{to} - Spill_{ij,t}^{from}. \tag{9}$$

If $NPS_{ij,t} > 0$ ($NPS_{ij,t} < 0$), variable i has a stronger impact on variable j than vice versa implying that variable i dominates variable j.

Next we demonstrates the joint connectedness approach following Lastrapes and Wiesen (2021). The equivalent of $C_{"\rightarrow i,t}^{from}$ for the joint connectedness approach is equal to:

$$C^{jnt,from}_{\bullet\to i,t} = \frac{E\left(\Psi^2_{i,t}(H)\right) - E[\Psi_{i,t}(H) - E\left(\Psi_{i,t}(H)\right) \,|\in_{\forall\neq i,t+1},\ldots,\in_{\forall\neq i,t+H}]^2}{E\left(\Psi^2_{it}(H)\right)} = \frac{\sum_{h=0}^{H-1} \boldsymbol{e}_i' B_{ht}\,\Sigma_t\, M_i\left(M_i'\,\Sigma_t\, M_i'\right)^{-1} M_i'\,\Sigma_t\, B_{ht}' e_i}{\sum_{h=0}^{H-1} e_i' B_{ht}\,\Sigma_t\, B_{ht}' e_i} \tag{10}$$

Which is the proportion of the *H*-step forecast error variance of variable *i* that can be explained by jointly conditioning on the future shocks of all non-*i* variables. Here, *Mi* is a $N\times N-1$ that equals the with the *i* th column eliminated, and $\in \forall \neq i, t+1$ denotes the *N*−1 dimensional vector of shocks at time *t*+1 for all variables except variable *i*.

Note that no normalization is required to ensure that the spillovers are within zero and unity opposed to the original connectedness approach. The joint total connectedness index is formulated by:

$$TSpill^{jnt}_t = \frac{1}{N}\sum_{i=1}^{N} C^{jnt,from}_{i\leftarrow",t} \tag{11}$$

However, the main problem with this approach is that it cannot compute the net directional pairwise spillovers which determine the bilateral strengths across variables which are essential for portfolio and risk management.

Balcilar et al. (2021) developed the extended joint connectedness approach which try to find the equivalence of $Spill_{ij,t}$ for the joint connectedness approach, namely $Spill^{jnt}_{ij,t}$ which allows to calculate the net pairwise directional connectedness measures and fulfills the following conditions:

$$C^{jnt,from}_{i\leftarrow\bullet,t} = \sum_{j=1,j\neq i}^{N} Spill^{jnt}_{ij,t} \tag{12}$$

$$C^{jnt,to}_{\bullet\leftarrow i,t} = \sum_{j=1,i\neq j}^{N} Spill^{jnt}_{ji,t} \tag{13}$$

$$TSpill^{jnt}_t = \frac{1}{N}\sum_{i=1}^{N} C^{jnt,from}_{i\leftarrow\bullet} = \frac{1}{N}\sum_{i=1}^{N} C^{jnt,to}_{i\to\bullet} \tag{14}$$

For this purpose, we have to to generalize the scaling approach of Lastrapes and Wiesen (2021). This in turn means that the suggested calculation of Eq. 13 has to be true. Since the row sum of the original and the joint connectedness table has to be equal to 1, the diagonal elements of the joint connectedness table need to stay the same as well. Thus, the scaling factor λ has differ by each row, resulting in the following equations:

$$\lambda_i = \frac{C^{jnt,from}_{i\leftarrow\bullet,t}}{C^{from}_{i\leftarrow\bullet,t}} \tag{15}$$

$$\lambda = \frac{1}{N}\sum_{i=1}^{N}\lambda_i \tag{16}$$

Finally, the following steps has to be programmed:

$$Spill^{jnt}_{ij,t} = \lambda_i Spill_{ij,t} \tag{17}$$

$$Spill^{jnt}_{ii,t} = 1 - C^{jnt,from}_{i\leftarrow",t} \tag{18}$$

$$C^{jnt,to}_{i\to",t} = \sum\nolimits_{j=1,i\neq j}^{N} Spill^{jnt}_{ji,t} \tag{19}$$

Finally, allowing the scaling parameter to vary by row allows to compute the net total and pairwise directional connectedness measures as follows:

$$NET^{jnt}_{i,t} = C^{jnt,to}_{i\to",t} - C^{jnt,from}_{i\leftarrow",t} \tag{20}$$

$$NPS^{jnt}_{ij,t} = Spill^{jnt,to}_{ji,t} - Spill^{jnt,from}_{ij,t}. \tag{21}$$

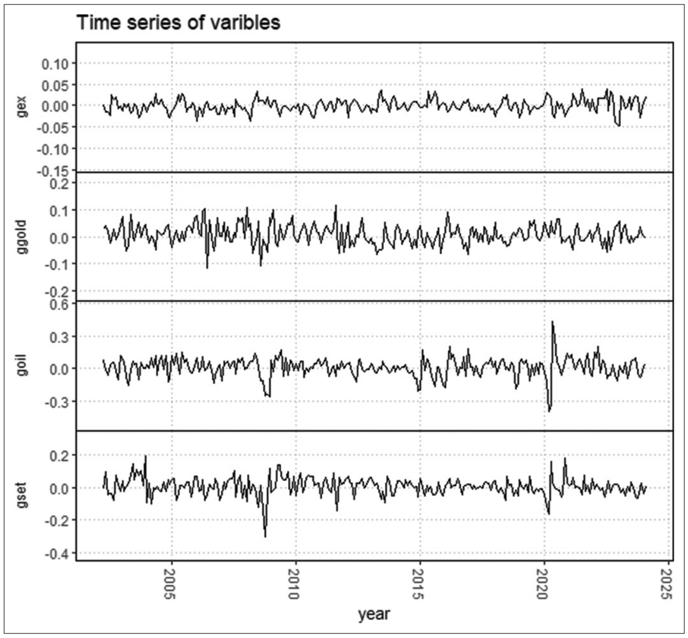
4. RESULTS

Since our studied variables—the crude oil price index (oil), gold price (gold), stock price index(set), and Thai-Baht exchange rate(ex)—are not stationary in level, as determined by the unit root test statistics developed by Elliott et al. (1996), we must employ the first log-differenced series, which can be interpreted as the percentage change of these variables. Figure 1 illustrates the patterns of these series with "g" added to each variable. The patterns of all returns show similar trends, especially before 2010, and the oil and stock market returns are closely related during 2020.

Table 1 shows the descriptive statistics of the data used in the study. All series are in the form of log difference meaning log percentage change. When considering the average values, it can be found that in general, the return of oil, gold, and stock have changes in an increasing direction except for the exchange rate. For the volatility, it can be seen that the oil is the most volatile variable with a variance value of 0.0081 while the least volatile variable is the exchange rate, with a variance of 0.0002. This may be due to Thailand's policy of maintaining the exchange rate within a framework that does not affect the stability of the economic. Skewness and kurtosis testing indicates that the series are not normally distributed, both oil (ggoil) and stock (gset) exhibit left-skewed variables, while gold price (ggold) and exchange rate (gex) display right-skewed distributions. Additionally, both oil (ggoil) and stock (gset) returns follow leptokurtic distributions, suggesting heavier tails and sharper peaks compared to a normal distribution. As the normality test using Jarque and Bera (1980), the oil (ggoil) and stock (gset) returns are significantly non-normally distributed. According to the ERS unit root test of Elliott et al. (1996), all returns are stationary, at least on the 1% significance level. From Fisher and Gallagher (2012)'s weighted portmanteau test, they shows that the percentage changes in all variables and their squared returns are autocorrelated, supporting our decision to model the interconnectedness of the series using a TVP-VAR approach with a time-varying variance–covariance structure.

Table 2 presents the pairwise correlation matrix of the variables in the model. All variables, except for the exchange rate, exhibit

Figure 1: Time series of variables in term of log difference



positive correlation coefficients, indicating a positive correlation between the returns of gold, oil, and the stock market. Among the correlation pairs, oil prices exhibit the strongest positive correlation with stock market returns, with a correlation coefficient of about 0.1572. Additionally, the table demonstrates a positive relationship between gold and stock market returns with a correlation coefficient of 0.1084. Overall, while some correlations may be weak, they provide insights into the direction and strength of relationships between the variables, aiding in understanding their potential interdependencies within the dataset.

The dynamic linkage results for all variables in the system under the study are presented as follows. We start by reporting the average TCI values, followed by the pattern of the TCI over the studied period. Then, we analyze the net total connectedness and net pairwise connectedness results to gain deeper insights into the role of each market within our proposed system.

4.1. Average Dynamic Extended Joint Connectedness

Table 3 presents the average value of the total connectedness between different assets, which is obtained by TVP-VAR model forecast error variance decomposition. It reveals how volatility is distributed between variables, with diagonal elements representing self-explanatory behavior. Off-diagonal values indicate the proportion of forecast error variance attributed to and from innovations in other variables. Volatility Spill-over (FROM) shows how rows are influenced by column variables, whereas Volatility Spill-over (TO) shows how column variables affect rows. For example, "goil" has approximately 84.21% of its forecast error variance originating from its own shocks, with 15.79% traceable to "ggold," "gset," and "gex" innovations. The total averaged connectedness index (TCI) is 24.01%, indicating that the network of all variables can explain 24.01% of changes within the network. Notably, idiosyncratic effects can account for approximately 76% of the system's prediction error variation.

Table 1: Descriptive statistics of variables

Statistics	Variables			
	goil	ggold	gset	gex
Mean	0.0087	0.008	0.0065	−0.0006
Minimum	−0.3976	−0.1173	−0.3018	−0.0451
Maximum	0.4321	0.1184	0.1952	0.0392
Variance	0.0081	0.0014	0.0031	0.0002
Skewness	−0.4215***	0.1036	−0.4759***	0.0161
P	−0.005	0.4799	0.0019	0.9124
Ex_Kurtosis	3.7057***	0.393	3.9529***	0.1319
P	0.0000	0.1549	0.0000	0.4767
JB	162.5511***	2.3993	185.9107***	0.2776
P	0.0000	−0.3013	0.0000	−0.8704
ERS	−2.3701	−2.243	−4.6834	−4.3931
Q (10)	29.3131***	8.074	10.217	36.048***
P	0.0000	0.16445	0.0633	0.0000
Q2 (10)	145.7277	19.9017	17.5969	32.5637***
P	0.0000***	0.0004***	0.0013	0.000***

***,**,*denote significance level at 1%, 5% and 10%; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit-root test; Q (12) and Q2 (12): Fisher and Gallagher (2012) weighted portmanteau test

Table 2: Pairwise correlation

Variables	goil	ggold	gset	gex
goil	1.0000			
ggold	0.0714	1.0000		
gset	0.1572	0.1084	1.0000	
gex	−0.1290	−0.4261	−0.3643	1.0000

Table 3: Average joint connectedness table

Variables	goil	ggold	gset	gex	FROM
goil	84.21	2.71	10.95	2.14	15.79
ggold	1.60	79.73	5.42	13.25	20.27
gset	2.92	2.7	81.93	12.45	18.07
gex	3.21	16.52	22.17	58.1	41.9
TO	7.73	21.92	38.54	27.84	96.03
Inc.Own	91.93	101.65	120.47	85.95	TCI
NET	−8.07	1.65	20.47	−14.05	24.01

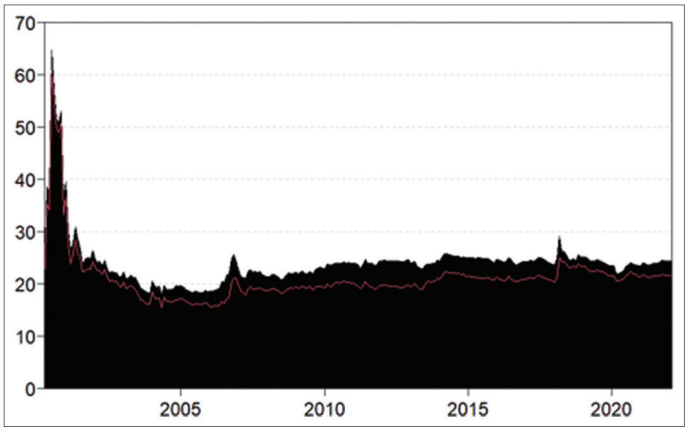
Results are based on a TVP-VAR model with a lag length of order one and a 10-step-ahead generalized forecast error variance decomposition. TVP-VAR: Time-varying parameter vector autoregression model, TCI: Total connectedness index

It is important to remember that the previous average results merely provide an overview of the interlinkages of the studied system. To completely comprehend the effects on interlinkages throughout a network of all variables, a more dynamic analysis framework is required. Figure 2 displays the dynamic of Total Connectedness Index (TCI) across time in order to illustrate the response of the TCI to the different economic or political situations during the period of the study. In Figure 3, it is critical to evaluate changes in the behavior of a specific variable as it transitions between being a net shock transmitter and a net shock receiver, and vice versa. Note that positive numbers imply a net transmitting role, while negative values signify a net receiving role. Our subsequent research focuses on net pairwise connectivity estimations, as seen in Figure 4.

4.2. Dynamic Total Extended Joint Connectedness

The time variant of total connectedness (TCI) is illustrated in Figure 2. Higher TCI values indicate larger spillovers across assets, and high TCI values also imply significant contagions between the variables in the model. It can be seen that the TCI values vary remarkably across our studied sample period. The TCI exhibits relatively sizable values and oscillates at specific points at the beginning of our sample, with the highest peak reaching almost 70%. However, these TCI values tend to decline and then remain around 20%. Until 2008, spillovers across markets increase again, as evidenced by the substantial increase in market integration during the global financial crisis in 2008. Although TCI began to decline after peaking in 2008, there was high volatility again in the 2019-2020 period. The level of interconnectedness reached nearly 30% due to global events like the Oil Price Crash and Covid-19.

Figure 2: Dynamic total connectedness



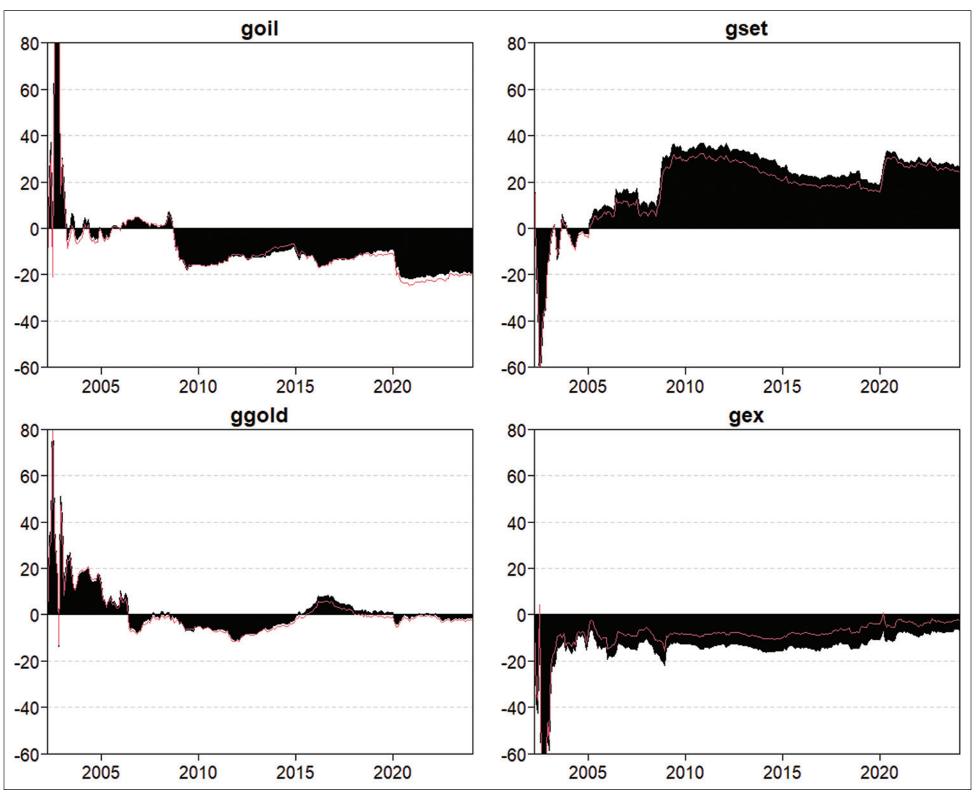
Results are based on a Time-Varying Parameter Vector Autoregression model with a lag length of order one and a 10-step-ahead generalized forecast error variance decomposition

4.3. Net Total Directional Connectedness

The results for the net total directional connectedness of each asset in Figure 3 provide us with a deeper insight into the role of each asset either as a net shock transmitter or a net shock receiver within our proposed model. It's worth noting that each asset has the potential to shift between these two roles.

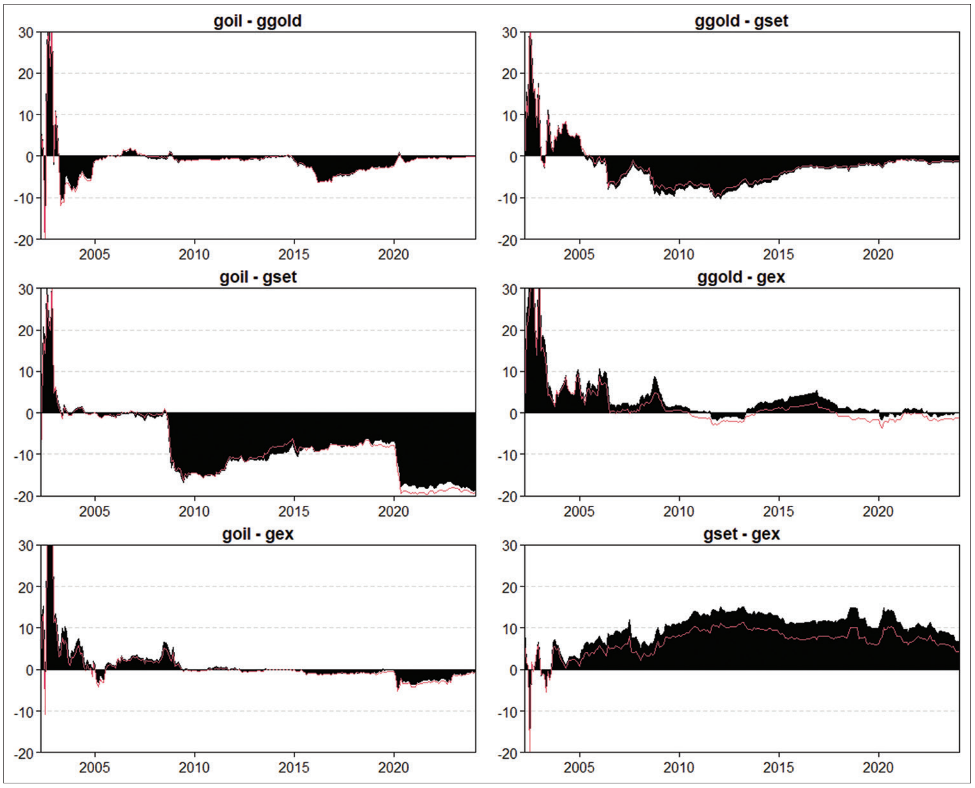
Focusing our attention on Thailand we can observe that oil return (goil) has been switching between a net transmitter and a net receiver for the first 8 years of the study then consistently appearing as a net receiver of shocks after 2008 (consistent with Nguyen et al., 2023). The exchange rate return (gex) consistently act as net contagion shock receivers all time studied. During the initial 5 years of our study period (2002-2007), Thailand's stock market (gset) plays a major net recipient of shocks. However, its role reverses to a net transmitter for the rest of the study period, with a sharp increase in its role in 2008-2009. Gold (ggold), by contrast, shift their roles over time. It is noticeable that, on average, stock return is the main net-transmitter of volatility, while exchange rate return is the main net-recipient of volatility. As a result of the connectedness from our data, it can be concluded that that exchange rate is the long-term net shock receiver, and stock return is the long-term shock transmitters.

Figure 3: Dynamic net total directional connectedness



Results are based on a Time-Varying Parameter Vector Autoregression model with a lag length of order one and a 10-step-ahead generalized forecast error variance decomposition. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line)

Figure 4: Dynamic net pairwise directional connectedness



Results are based on a Time-Varying Parameter Vector Autoregression model with a lag length of order one and a 10-step-ahead generalized forecast error variance decomposition. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line)

4.4. Net Pairwise Directional Connectedness

Next, we examine the net pairwise directional connectedness measures, with the results presented in Figure 4, calculated using Eq. (21). Initially, we focus on the spillover effect of gold (ggold) on oil (goil), as depicted in (goil-ggold). Before the 2008 global financial crisis, crude oil acted as both shock transmitter and receiver. However, post-2015, it becomes evident that oil returns primarily serve as the net recipient of shocks.

When analyzing the spillover effect of oil prices on stock returns (goil-gset), crude oil initially serves as a significant shock transmitter, particularly with high magnitude effect during first 3 years of study. However, since 2008, Thailand's stock market return has predominantly emerged as the primary transmitter of shocks to oil returns. A period of low magnitude was observed between 2012 and 2015, while periods of notably higher magnitude occurred between 2008 and 2010 and from 2019 onward, coinciding with the global financial crisis and the COVID-19 pandemic, respectively.

The spillover effects of oil on exchange rate markets are evidenced by the goil-gex. It's notable how the transmission dynamics have shifted over time. Initially, before 2010, oil was seen as a net transmitter of spillover effects to exchange rates. However, by 2020, this relationship had significantly reversed. In relation to all other pairwise connectedness, they do not seem to have considerable linkage in terms of magnitude during 2010-2020.

The evolution of spillover effects from gold returns to stock returns (ggold-gset) has been notable over time. Initially, a pattern of transmission from gold to the stock was observed before 2005, indicating gold plays as a net transmitter of shocks. However, this pattern reversed thereafter. Notably, since 2015, there has been a decreasing trend in the spillover effect of gold on stock returns. This suggests a changing dynamic in the relationship between gold and stock returns, with diminishing influence observed in recent years.

The examination of spillover effects between gold and exchange rate returns (ggold-gex) reveals a consistent pattern where gold returns predominantly act as a net shock transmitter to exchange rates. It is noteworthy that this phenomenon is most prominent in the early phases of the study period and gradually diminishes until around 2014. Subsequently, there is a notable increase in the spillover effect.

The analysis of spillover effects reveals a notable dynamic between the stock market and exchange rate (gset-gex). Throughout the study period, the stock market return is considered consistently as the net transmitter of shocks to exchange rate returns. This finding underscores the significant influence of the stock market on the broader macroeconomic landscape, particularly through its impact on exchange rates.

In summary, our findings demonstrate significant interconnectedness among oil, gold, stock, and exchange rate returns. Policymakers and investors can utilize these results as early warning signals for potential spillover effects. Therefore, it is crucial to implement improved assets management strategies that do not solely focus on one asset.

5. CONCLUSION AND RECOMMENDATION

This study employs an extended joint connectedness TVP-VAR approach to examine the dynamic spillover of four markets: crude oil, gold, stocks, and exchange rates in Thailand. Monthly data from April 2002 to March 2024 are collected for analysis. The results demonstrate a time-varying linkage among variables in our system, indicating that shocks in one variable can influence others, thereby generating spillover risks to the entire system. Specifically, exchange rate returns are mainly influenced by stock and gold returns. Moreover, gold emerges as a volatile asset as its role is not persistent over our studied time period. Additionally, the results highlight a significant intensification of volatility during the global financial crisis in 2008.

These findings carry important policy implications. Firstly, due to the time-varying relationship between oil, gold, stock, and exchange rate returns, policymakers should monitor these four assets as a system. Changes in any one asset can impact the others, especially changes in the stock market, which can contribute to systemic risk. Secondly, the study reveals that the oil price is not the main factor influencing the performance of Thailand's stock and exchange rate markets. Instead, the stock market plays a significant role as a transmitter of spillover effects. These findings will help investors anticipate and manage currency risk associated with their portfolio investments.

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