Spillover Effects Between Commodity Markets, Financial Markets, and the Real Economy

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Abstract

This paper attempts testing linkage between oil market represented as commodity, stock market and international trade market, which is denoted as real economy. The analysis is based on daily market prices and indices from 1990 to 2022. The evidence from Vector autoregression models for linkages of them suggests that correlations are significant but none of the estimates are notably high, and while each market cannot be said to be uncorrelated to the other, it is difficult to conclude that there is a clear correlation. The hypothesis testing with the Granger causality indicates that the international trade market was not causal to the oil and stock markets, however, which is unexpected result from earlier survey. In terms of how each market reacted to the shocks, the oil and stock markets responded quickly, within approximately one day, while the international trade market took nearly 10 days to recover from the shocks. However, the empirical results in this paper are very few as one would expect from earlier studies, and one can infer confounding factors and sample selection issues behind this. Hopefully, this paper will serve as a warning for future empirical analysis of the linkage between oil markets, stock markets, and the real economy.

Keywords: Baltic Dry Index, Granger causality, Impulse response function, oil market

JEL Classification: C32, G13, F62, Q43, Q47

1. Introduction

In May 2022, the Federal Reserve Board (FRB) of the United States reported in its Financial Stability Report[1] that fluctuations in commodity markets such as energy resources and wheat due to the recent global situation may have an impact on financial institutions that handle these transactions. In particular, trends in energy resources and wheat are said to have a wide-ranging influence because they are related not only to economic activities but also to various aspects of our daily lives, and it is inevitable that financial institutions should be sensitive to these trends. On the other hand, attention has also begun to focus on "megatrends," macroeconomic trends that have the power to shape the state of the world, such as technological development and demographic trends associated with urbanization. It is observed in Goldstein and Yang's (2022) study that the interaction between commodity markets and the real economy is a complex combination of geopolitical factors associated with world affairs and overall economic trends.

In the industrial activities that underpin the economy, Dupoyet and Shank (2018) provide empirical evidence that oil prices actually have a positive and significant impact on three industries (manufacturing, energy, and utilities) and a negative and significant impact on two industries (consumer durables and wholesale trade). Also, in terms of exporting countries, Mehrara (2008) finds that oil revenue shocks tend to affect production asymmetrically and nonlinearly in oil-dependent countries, so that negative oil shocks have a negative impact on production, while positive oil shocks and booms have a limited role in stimulating economic growth suggesting that they play a role. It is understood from previous studies and reports that the oil market is relevant to economic activity and our lives, but it is interesting to consider how deeply it is related. However, when analyzing with the real economy, it faces a major hurdle. This is because it is unclear what values are indicative of the real economy. It is possible to understand corporate performance by focusing on stock prices and dividends, and it is also possible to understand trends in energy resources from changes in electricity and gas prices. Many studies provide empirical analysis and economic views based on it is observed stock prices and market prices of resources.

The economy is measured by GDP growth, interest rates (policy rates), or the consumer price index (CPI), but not by daily data like commodity markets or stock markets. The Baltic Dry Inde (BDI) is a good place to start. The BDI is a composite index calculated by the Baltic Dry Exchange in London from freight rates and charter rates for ocean-going tramp vessels that carry dry cargoes such as iron ore and grains, obtained from shipping companies and brokers around the world. Although the BDI is an index rather than a price, it is a system

[1] https://www.federalreserve.gov/publications/brainard-statement-20220509.htm

whereby ship freight rates increase and the index rises as demand for ships rises, and high demand for ships means that trade is flourishing and economic activity is active. In other words, by using this property of BDI as an indicator of the real economy, an empirical analysis can be expected to be conducted. Apergis and Payne (2013, IJFS) conducted a study on forecasting economic trends using BDI, suggesting the possibility of empirical analysis. Based on these studies, this paper focuses on West Texas Intermediate crude oil futures (WTI futures) and BDI, which are one of the energy resources and international benchmarks in the crude oil market, and the S&P 500 index (S&P 500) as a representative of the stock market, and examines how the crude oil market, stock market, and real economy are linked through empirical analysis. And explores the potential for linkages between the oil market, the stock market, and the real economy.

Given the current position of the commodity markets, this paper hopes that the relationship between the commodity markets, the financial markets, and the real economy when they are intermingled is research that is in line with reality, and aims to clarify whether there is a relationship between each of the three markets (more precisely, the two markets and the real economy), or whether the relationship is asymmetrical in only one direction, or no relationship at all. Referring to the work of Gong and Xu (2022), who state that commodity markets reflect geopolitical factors, the study will also examine how each market reacts to shocks when there is heightened uncertainty associated with historical financial or economic shocks that have occurred in the past. Based on these empirical analyses, this paper will also address the predictability of each market.

The empirical analysis in this paper will be conducted on the correlation between WTI futures, S&P 500 and BDI using the Vector autoregression model (VAR model), which is widely used in empirical analysis of multiple causal relationships, etc. The sample period is from before the Asian currency crisis to after the Covid-19 shock from January 1990 to April 2022. Next, using Granger causality tests to examine whether there have been changes in the causal relationships among markets during the three historical economic shocks: the Asian Currency Crisis (1996-2000), the Global Financial Crisis (2006-2010), and the Covid-19 pandemic (2018-2022). Finally, the response of each market to shocks in each period is observed using an Impulse response function to search for predictability.

The estimation results indicate that all markets have statistically significant correlations with each other. The empirical evidence supports the work of Gorton and Rouwenhorst (2006) and Wang and Xie (2012), who found that WTI futures prices have cross-correlations with several equity indices, such as the Dow Jones Industrial Average and the S&P 500. However, none of the estimates were remarkably high, and the correlations were very weak, although it cannot be said that each market was uncorrelated with the others.

The estimation results from the Granger causality test indicate that there was no Granger causality for BDI daily changes to WTI returns and S&P 500 returns, and it is observed that the reciprocal relationship between commodity markets and the real economy as noted by Goldstein and Yang (2022). On the other hand, as far as causality is concerned, the results support Baiardi et al. (2020), who provided empirical evidence of an asymmetric relationship between WTI futures and the S&P 500 index.

Finally, it is observed that the response of each market to shocks from the Impulse Response Function was remarkably weak. However, one characteristic point regarding the waveform of the shocks is that the response of the WTI return and the S&P 500 return to shocks converged in about one day, while the BDI daily changes took about 10 days to converge. This suggests that stock and commodity markets have high market liquidity, while trade markets are not as liquid.

The first reason why this paper did not provide the expected results is that the existence of Confounding factors can be inferred, suggesting that only superficial causality was detected. The second is that the S&P 500 was used as the empirical modeling for this paper. It can be inferred that this created the possibility of a strong linkage with WTI futures, which is also a benchmark for the U.S. crude oil market, thus weakening the linkage and causality with BDI. The empirical results obtained by this paper are expected to provide a contribution as a caution in adjusting for confounding factors and selecting an appropriate sample when conducting empirical analysis with the real economy in future.

Briefly describing the structure of this paper. Chapter 2 summarizes studies that have conducted empirical analysis on the correlation between the WTI futures market and the stock market or the real economy, as well as studies that have conducted empirical analysis on multiple markets at the same time; Chapter 3 describes the empirical modeling used in this paper; Chapter 4 discusses the sample data for the analysis and examines whether the sample data are suitable for empirical analysis. Chapter 5 first describes the estimation results from the empirical modeling, next describes the causality among markets for each specific time period, and then describes the empirical results from the Impulse Response Function. Finally, Chapter 6 provides discussion and conclusions based on the empirical results.

2. Literature review

Research on commodities, including crude oil, has tended to be dominated by studies on the correlation between commodity markets and stock markets through the work of Bodie and Rosansky (1980), who provided a discussion of whether risk diversification is effective, Cheung and Miu (2010), and Jensen et al. (2000). From there, it was extended to financial markets, including stock markets, debt markets, and exchange rate markets, as in the case of the empirical study of the correlation with U.S. inflation and expected inflation provided by Gorton and Rouwenhorst (2006) and the study of the correlation with crude oil provided by Ferraro et al. (2015), which used crude oil prices to forecast exchange rates, gradually emerged from a macro perspective. Other studies include Kilian and Park (2009), who studied the stock market response in the United States to oil price shocks; Wen et al. (2019) and Cheng et al. (2019), who studied the relationship between oil price shocks and the Chinese economy and its response. Alola (2021), who analyzed the dynamics of oil prices and the country's real estate market in Saudi Arabia, and Phoong et al. (2020), who analyzed the relationship between GDP and Brent oil prices in Malaysia. Thus, country-specific empirical studies on the real economy have already been pioneered by many scholars. The background of these studies can be assumed to be that researchers are interested in how commodities that are deeply related to our daily lives, such as electricity and bread, are related from a macro perspective.

In addition, studies have been conducted on the linkages between markets and their strength, including the linkages between commodity markets and financial markets and volatility spillover effects (see Johnson and Soenen (2009, EMFT), Mensi et al. (2013, EM), Ildirar and Iscan (2016 IJEFS). Corbet et al. (2021), who conducted an empirical analysis of the negative price of WTI crude oil futures and its volatility spillover effect under the impact of Covid-19 and another study by Ahmed and Sarkodie (2021), who conducted an empirical analysis of the impact of economic shocks and economic policy uncertainty caused by COVID-19 across multiple commodity markets, including the crude oil market. These studies suggest that research reflecting the real economy has begun to be conducted in recent years. As mentioned in the introduction, the fact that daily data showing the real economy are scarce compared to stock and commodity markets suggests that research on linkages among multiple markets with the real economy has tremendous potential. Therefore, in this paper, using BDI as an indicator of the real economy to attempts to clarify the relationship between WTI futures and the S&P 500 through empirical modeling.

3. Empirical modelling

Earlier studies on commodity markets, stock markets, and the real economy have provided evidence of correlations such as those between commodity markets and stock markets or stock markets and the real economy, but studies involving all three markets appear to be underdeveloped. In addition, based on Goldstein and Yang's (2022) empirical analysis of the correlation between the commodity markets and the real economy, it can be expected that a longer period of analysis would allow us to observe the impact of the real economy on the commodity markets. Therefore, this empirical analysis will employ empirical modeling based on the VAR model derived by Sims (1980) as a method that can examine all three markets together.

First, before explaining the empirical modeling, an explanation is given regarding the variable y used in the estimation. Since the WTI futures price, which is one of the targets of this analysis, has recorded a negative price, the following equation for daily changes is used instead of log returns. The daily changes[2] $y_{i,t}$ of each market is as in equation (1), where $p_{i,t}$ is the daily price (or daily data) of each market at time t.

$$\begin{cases} y_1 = \dfrac{p_{WTI,t} - p_{WTI,t-1}}{p_{WTI,t-1}} \\ y_2 = \dfrac{p_{BDI,t} - p_{BDI,t-1}}{p_{BDI,t-1}} \\ y_3 = \dfrac{p_{S\&P500,t} - p_{S\&P500,t-1}}{p_{S\&P500,t-1}} \end{cases} \tag{1}$$

The empirical modeling using equation (1) is as follows in equation (2).

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix} + \Phi_1 \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + \Phi_2 \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix}, \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix} \sim W.N.(\Sigma) \tag{2}$$

Equation (2) is called the tri-variate VAR(2) model[3], where $C_i, i = 1,2,3$ are exogenous variables and Φ_1, Φ_2 and Σ are represented by equations (3), (4) and (5) , respectively.

$$\Phi_1 = \begin{bmatrix} \phi_{11}^{(1)} & \phi_{12}^{(1)} & \phi_{13}^{(1)} \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} & \phi_{23}^{(1)} \\ \phi_{31}^{(1)} & \phi_{32}^{(1)} & \phi_{33}^{(1)} \end{bmatrix} \tag{3}$$

$$\Phi_2 = \begin{bmatrix} \phi_{11}^{(2)} & \phi_{12}^{(2)} & \phi_{13}^{(2)} \\ \phi_{21}^{(2)} & \phi_{22}^{(2)} & \phi_{23}^{(2)} \\ \phi_{31}^{(2)} & \phi_{32}^{(2)} & \phi_{33}^{(2)} \end{bmatrix} \tag{4}$$

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[2] In this paper, daily changes in WTI futures and the S&P 500 will be denoted as returns and daily changes in BDI will be denoted as daily changes.

[3] The VAR (2) model was used according to the Schwartz Information Criterion (SC) of the Lag Length Criteria. See Appendix for test results.

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} \tag{5}$$

In addition, $\varepsilon_{i,t}, i = 1,2,3$ in equation (2) does not take into account the correlation among the error terms, so simultaneous constraints must be performed to estimate using the Impulse Response Function in this paper. First, triangular decomposition of Σ is performed according to equation (6). D in equation (6) is a certain diagonal matrix.

$$\begin{gathered} \Sigma = ADA^T \\ , A = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix} \end{gathered} \tag{6}$$

Second, the orthogonalized disturbance term u_t is derived from equation (6) as equation (7).

$$u_t = A^{-1}\varepsilon_t \tag{7}$$

Then, from equation (7), the variance-covariance matrix of u_t can be expressed as in equation (8).

$$var(u_t) = E(u_t, u_t^T) = A^{-1}E(\varepsilon_t, \varepsilon_t^T)(A^T)^{-1} = D \tag{8}$$

Finally, from equation (8), each component of u_t can be said to be uncorrelated at the same time, and ε_t can be decomposed into uncorrelated shocks u_t. Therefore, this empirical modeling can be expressed as in equation (9), and the Impulse Response Function of $y_{i,t+k}$ to $u_{j,t}$ is defined as in equation (10).

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix} + \Phi_1 \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + \Phi_2 \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix}, \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \end{bmatrix} \sim W.N.(\mathrm{D}) \tag{9}$$

$$IRF_{ij}(k) = \frac{\partial y_{i,t+k}}{\partial u_{j,t}} \tag{10}$$

The null hypothesis by Granger causality test is estimated in equation (2) by estimating $y_{i,t}$, $i = 1,2,3$ by OLS and the residual sum of squares is SSR_1,and the residual sum of squares of those estimated by OLS in the same way with constraints imposed is SSR_0,using equation (11).

$$F \equiv \frac{(SSR_0 - SSR_1)/_r}{SSR_1/_{(T - np - 1)}} \tag{11}$$

4. Data description

Figure 1 plots the prices of WTI, BDI, and the S&P 500 and their daily changes in a time series. From Figure 1, it can be seen that the WTI market and BDI changes appear to be linked, and it can be inferred that there is a correlation between the commodity markets and the real economy. It can also be expected from Figure 1 that the volatility of the oil market, as noted by Dutta (2017), is higher than the volatility of the stock market, although this is difficult to recognize because the volatility of the WTI return is very high at a given point in time. Otherwise, it can be inferred from the daily changes that the volatility clustering of WTI, BDI, and the S&P 500 seems to be linked to the time of year in which it occurs.

Figure-1 Daily prices and changes on WTI, BDI and S&P500: 1990-2022

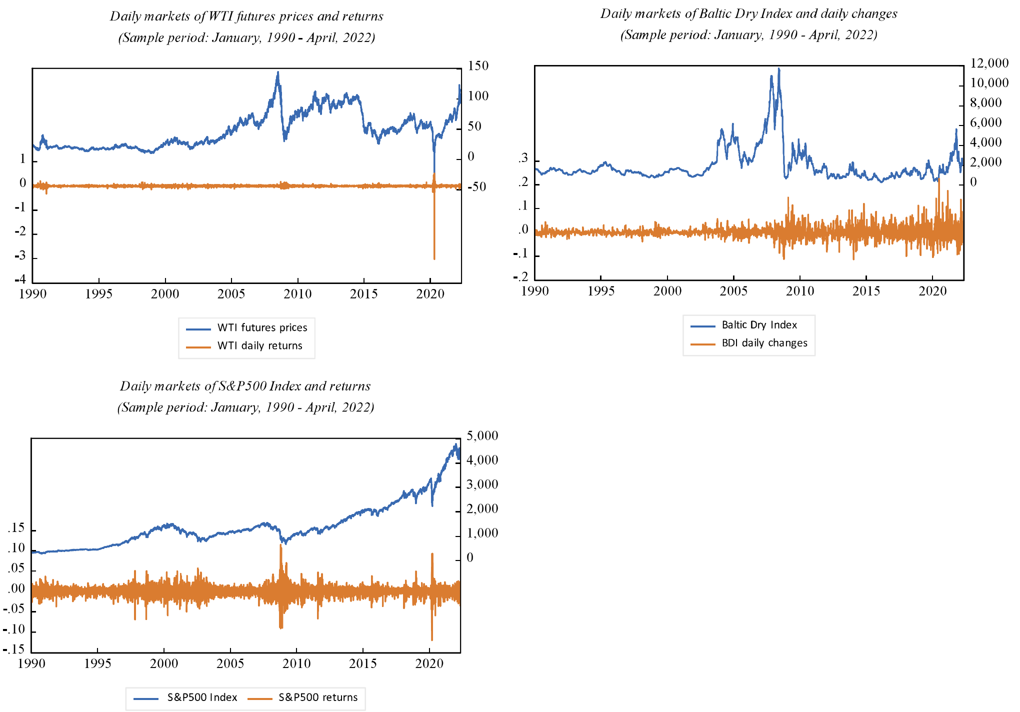


Table 1 summarizes the distributional characteristics of WTI returns, BDI daily changes and S&P 500 returns and the estimation results from the Jarqu-Bera and Augmented Dickey-Fuller tests (ADF test). Table 1 suggests that the ADF test allows us to reject each data as a unit root at the 1% significance level, which is favorable for empirical analysis.

Finally, all sample data, WTI futures prices, BDI, and S&P 500, were obtained from the

Thomson Reuters database on a daily basis, with the analysis period covering January 1990 through April 2022. In order to observe whether the causality among markets has changed under multiple historical economic shocks, the period 1996-2000, including the Asian Currency Crisis, 2006-2010, including the Global Financial Crisis, and 2018-2022, including the pandemic caused by Covid-19, are also included separately in the analysis period.

Table 1. Distributional moments of daily markets returns and changes in WTI, BDI and S&P500.

Distributional Properties	Mean	Std. Dev.	Skewness	Kurtosis	Jarque Bere	ADF test
WTI returns	0.00012	0.04455	-39.1765	2580.4850	2.34E+09	-20.7809***[c]
BDI daily changes	0.00023	0.01911	0.79029	13.65362	40763.59	-29.8644***[c]
S&P500 returns	0.00036	0.01123	-0.18904	14.37268	45501.71	-100.136***[a]

Notes: The sample period of daily observation runs from July, 1990 to April, 2022. Significance at 1 % level is denoted by *** under the MacKinnon (1996)'s one-sided probability values. The stationarity of time series is estimated with the Augmented Dickey-Fuller methodology with intercept only, with both intercept and trend terms, and with neither intercept nor trend terms are denoted by superscripts a, b and c, respectively. Jarque-Bera statistics for normally tests are distributed as χ^2on the null.

5. Empirical evidence

Chapter 5 presents the estimation results from the VAR model, the hypothesis testing results from the Granger Causality Test, and the response of each market to shocks using the Impulse Response Function.

5-1. Estimated results by VAR modelling

Table 2 summarizes the results estimated using the empirical model described in Chapter 3. The statistical significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively, meaning that the Akaike information criterion is AIC and the Schwartz information criterion is SC.

WTI returns were statistically significantly positively correlated with WTI returns one period prior and statistically significantly negatively correlated with WTI returns two periods prior at a 5% level of significance. It was also a statistically significant negative correlation at the 5% level of significance with the BDI daily change one period prior, and a statistically significant positive correlation at the 5% level of significance with the BDI daily change two periods prior. The estimation results also revealed a statistically significant negative correlation with the S&P 500 return one period prior at the 5% level of significance and a statistically significant negative correlation with the S&P 500 return two periods prior at the 5% level of significance. Although all coefficients were statistically significant, the estimated values of each coefficient suggest that one period prior WTI return, two periods prior WTI return, and one period prior S&P 500 return have an effect on WTI return.

Table 2. Results estimated with VAR modelling during 1990 – 2022.

Sample period: January, 1990 – April, 2022			
Parameters	WTI returns	BDI daily change	S&P500 returns
WTI returns (t-1)	0.218923** (0.01085)	0.004414*** (0.00324)	0.002187*** (0.00280)
WTI returns (t-2)	-0.132567** (0.01085)	0.005402*** (0.00324)	-0.001557*** (0.00280)
BDI daily changes (t-1)	-0.071617** (0.03618)	0.822235** (0.01081)	-0.016843*** (0.00933)
BDI daily changes(t-2)	0.055532** (0.03617)	-0.127584** (0.01081)	0.017827*** (0.00933)
S&P500 returns (t-1)	-0.110175** (0.04243)	0.031210** (0.01268)	-0.088797** (0.01095)
S&P500 returns (t-2)	-0.001697** (0.04246)	0.012277** (0.01269)	-0.011100** (0.01095)
C	0.000145*** (0.00047)	5.34E-05*** (0.00014)	0.000388*** (0.00012)
AIC	-3.438578	-5.854357	-6.148151
SC	-3.432733	-5.848513	-6.142306

Notes: The estimated Vector autoregressive model is represented by equation:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix} + \Phi_1 \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + \Phi_2 \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix}.$$

y_1 represents daily returns on WTI, y_2 represents daily changes on BDI and y_3 represents daily returns on S&P500. The sample period of daily observation runs from January, 1990 – April, 2022. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively. Figures in round brackets represent probability values.

Next, BDI daily changes were statistically significantly positively correlated with WTI returns one period prior and statistically significantly positively correlated with WTI returns two periods prior at a 1% level of significance. It was also statistically significantly positively correlated with the BDI daily changes one period ago at a 5% level of significance, and statistically significantly negatively correlated with the BDI daily changes two periods ago at a 5% level of significance. The estimation results then revealed a statistically significant positive correlation at the 5% level of significance with the S&P 500 return one period ago, and a statistically significant positive correlation at the 5% level of significance with the S&P 500 return two periods prior. Although all coefficients were statistically significant, the estimated values of each coefficient suggest that the BDI daily change one period prior and the BDI daily change two periods ago have an impact on the BDI daily change. Table 2 shows that the correlation with the daily change in BDI one period prior is particularly strong.

Finally, S&P 500 returns were statistically significantly positively correlated with WTI returns one period prior and statistically significantly negatively correlated with WTI returns two periods prior at a 1% level of significance. It was also statistically significantly negatively correlated with the BDI daily change one period prior and statistically significantly positively correlated with the BDI daily change two periods prior at a 1% level of significance. The estimation results then revealed a statistically significant negative correlation at the 5% level of significance with the S&P 500 return one period prior, and a statistically significant negative correlation at the 1% level of significance with the S&P 500 return two periods prior. Although all coefficients were statistically significant, the estimates of each coefficient suggested that the one-period-ahead S&P 500 return was the most influential, but the estimates were still small.

5-2. Results of Granger Causality test

Table 3 shows the results of Granger causality tests for each period for causality to WTI returns, causality to BDI daily changes, and causality to S&P 500 returns.

For the period 1996-2000, which includes the Asian currency crisis, the estimation results are statistically significant at the 10% level only for the S&P 500 return relative to the daily change in BDI. The estimation results for 2006-2010, which includes the Global Financial Crisis, are statistically significant at the 1% significance level for the S&P 500 return relative to the WTI return and statistically significant at the 1% level for the S&P 500 return relative to the BDI daily change. Estimation results for 2018-2022, including the pandemic by Covid-19, were statistically significant at the 1% level of significance for S&P 500 returns relative to WTI returns and statistically significant at the 5% level of significance for WTI returns relative to S&P 500 returns. Finally, the estimation results for the whole period, 1990-2022, were statistically significant at the 5% significance level for the S&P 500 return relative to the WTI return, and statistically significant at the 10% significance level for the WTI return relative to the BDI daily change, and statistically significant at the 5% significance level for the S&P 500 return relative to the BDI daily change, respectively.

Table 3. Results of Granger Causality test

Explanatory variable	Asia Financial Crisis (1996-2000)	Global Financial Crisis (2006-2010)	Covid-19 pandemic (2018-2022)	Total period (1990-2022)
Dependent variable: WTI returns				
BDI daily changes	0.451493	2.664142	2.510238	3.936003
S&P500 returns	4.300081	17.50397***	10.14581***	6.773990**
Dependent variable: BDI daily changes				
WTI returns	3.417450	3.753143	0.896940	5.706401*
S&P500 returns	8.925437*	6.592567***	1.234151	6.640670**
Dependent variable: S&P500 returns				
WTI returns	2.340883	3.564107	7.147216**	0.781760
BDI daily changes	3.831570	1.945912	3.136374	4.009128

Notes: Estimating with Granger causality test is represented by equation: $F \equiv \frac{(SSR_0 - SSR_1)/r}{SSR_1/(T-np-1)}$.

The sample period of daily observation estimated with runs from July 1, 2008 to December 31, 2021. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively. The hypothesis tests are based on Granger Causality test following the F-test statistic.

5-3. Results estimated with Impulse Response Function

Figure 2 depicts the waveforms of the shocks estimated using the Impulse Response Function for the period from 1990 to 2020: a one standard deviation shock in the WTI return had a positive impact (0.04%) on the WTI return on the same day and disappeared after about five days. The one standard deviation shock in the WTI return has a slightly negative (-0.001% and -0.001%) impact on the BDI daily change and S&P 500 return, both one day later. Second, the one standard deviation shock in the BDI daily change has a positive impact (0.013%) on the BDI daily change on the same day and disappears after 10 days. Also, one standard deviation shocks in the BDI daily change had a positive impact (0.001% and 0.0004%) on both WTI and S&P 500 returns two to three days later, peaking at 0.001% and 0.0004%, respectively, and disappearing after seven days. Finally, a one standard deviation shock to the S&P 500 return had a positive impact (0.011%) on the S&P 500 return on the same day and disappeared after about three days. A one standard deviation shock to the S&P 500 return has a positive (0.001%) impact on the WTI return on the same day and a one day lagged negative (-0.0002%) impact on the daily change in BDI, which disappears after about four days. It is observed from the Impulse Response Function that the impact of a shock in one market on other markets over a 30-year period was significantly weak (small).

Figure – 2　Impulse response on daily markets during 1990-2022.

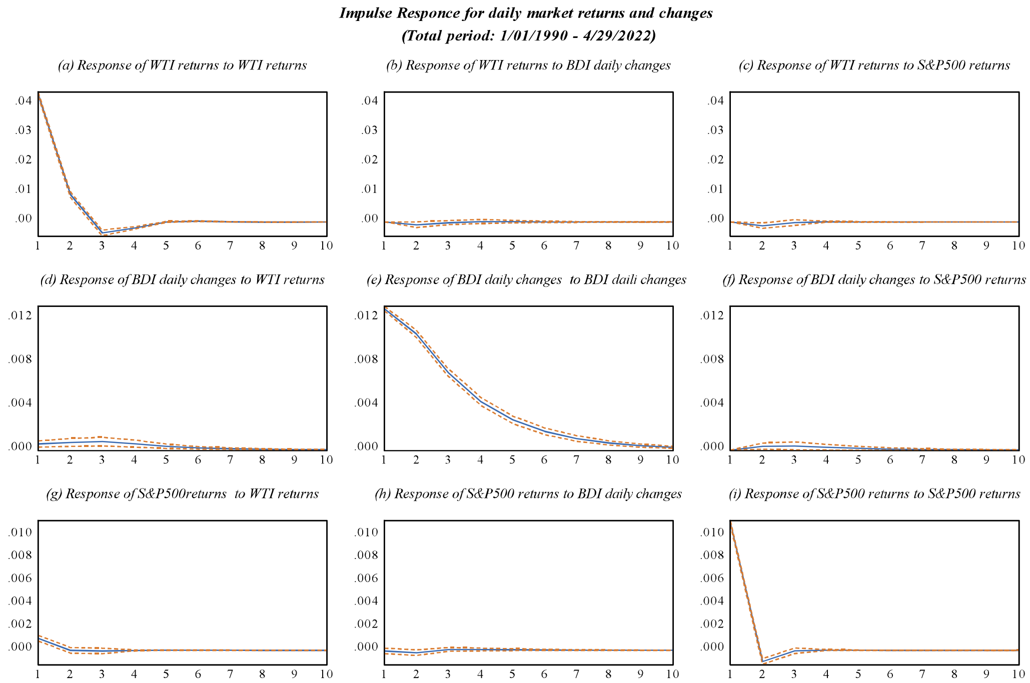
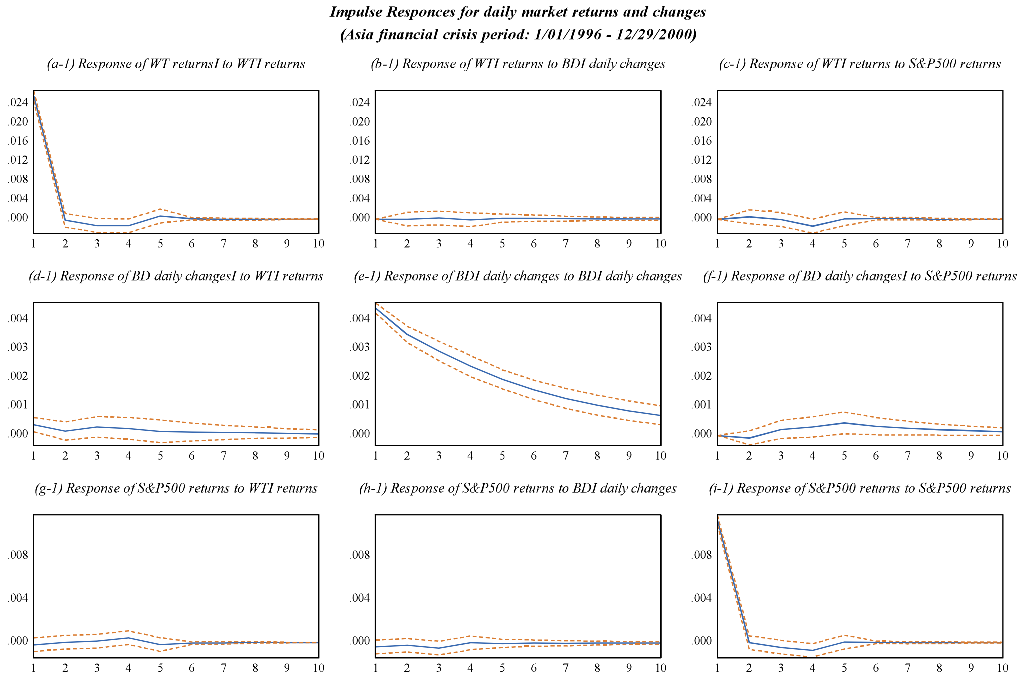


Figure 3 depicts the waveforms of shocks estimated using the Impulse Response Function for the period from 1996 to 2000, including the Asian currency crisis, where a one standard deviation shock in WTI return had a positive (0.099%) impact on WTI return on the same day. A one standard deviation shock in WTI returns had a negative (-0.005%, -0.009%) impact on BDI daily changes and S&P 500 returns one day later. Second, a one standard deviation shock in BDI daily change has a positive impact (0.023%) on BDI daily change on the same day, which disappears after 10 days. Also, a one standard deviation shock in the daily change in BDI had a positive impact (0.016%) on the WTI return on the same day, which lasted for three days and then disappeared. In contrast, it has a negative impact (-0.001%) on the S&P 500 return two days later. Finally, a one standard deviation shock in the S&P 500 return had a positive impact (0.013%) on the S&P 500 return on the same day, a negative impact the next day, and a positive impact again two days later. On the other hand, a one standard deviation shock in the S&P 500 return had a positive impact (0.001%) on the WTI return on the same day and a negative impact (-0.0006%) on the BDI daily change one day later.

Figure – 3　Impulse response on daily markets during 1996-2000.



A one standard deviation shock in WTI returns had a negative (-0.005%, -0.009%) impact on BDI daily changes and S&P 500 returns one day later. Second, a one standard deviation shock in BDI daily change has a positive impact (0.023%) on BDI daily change on the same day, which disappears after 10 days. Also, a one standard deviation shock in the daily change in BDI had a positive impact (0.016%) on the WTI return on the same day, which lasted for three days and then disappeared. In contrast, it has a negative impact (-0.001%) on the S&P 500 return two days later. Finally, a one standard deviation shock in the S&P 500 return had a positive impact (0.013%) on the S&P 500 return on the same day, a negative impact the next day, and a positive impact again two days later. On the other hand, a one standard deviation shock in the S&P 500 return had a positive impact (0.001%) on the WTI return on the same day and a negative impact (-0.0006%) on the BDI daily change one day later.

Figure 4 illustrates the waveforms of shocks estimated using the Impulse Response Function for the period from 2006 to 2010, which includes the Global Financial Crisis.
A one standard deviation shock in the WTI return had an impact (0.025%) on the WTI return on the same day. A one standard deviation shock in the WTI return had a positive (0.0004%) three-day lagged effect on the BDI daily change and a positive (0.002%) one-day lagged effect on the S&P 500 return. Second, a one standard deviation shock in the BDI daily change had a positive effect (0.013%) on the BDI daily change on the same day, and then increased slightly the next day and disappeared about 10 days later. Also, a one standard deviation shock

in the BDI daily change had a positive impact (0.001% and 0.001%) on the WTI return and the S&P 500 return two days later. Finally, a one standard deviation shock in the S&P 500 return had a positive impact (0.014%) on the S&P 500 return on the same day. A one standard deviation shock in the S&P 500 return had an impact (0.005%) on the same day's WTI return and a one day lagged negative impact (-0.0004%) on the BDI daily change.

Figure – 4　Impulse response on daily markets during 2006-2010.

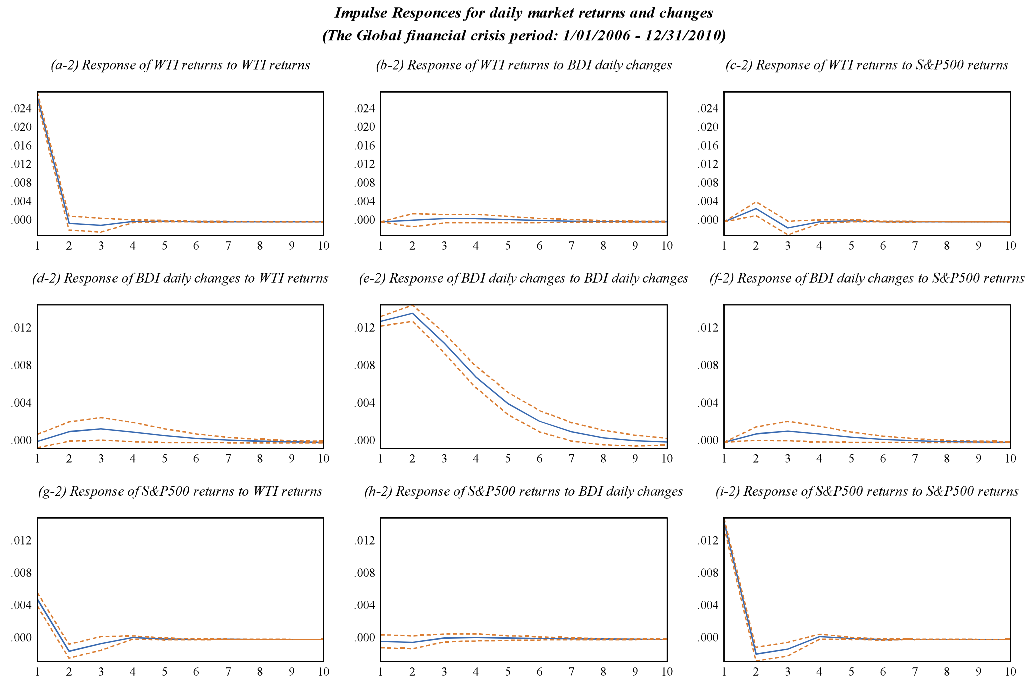
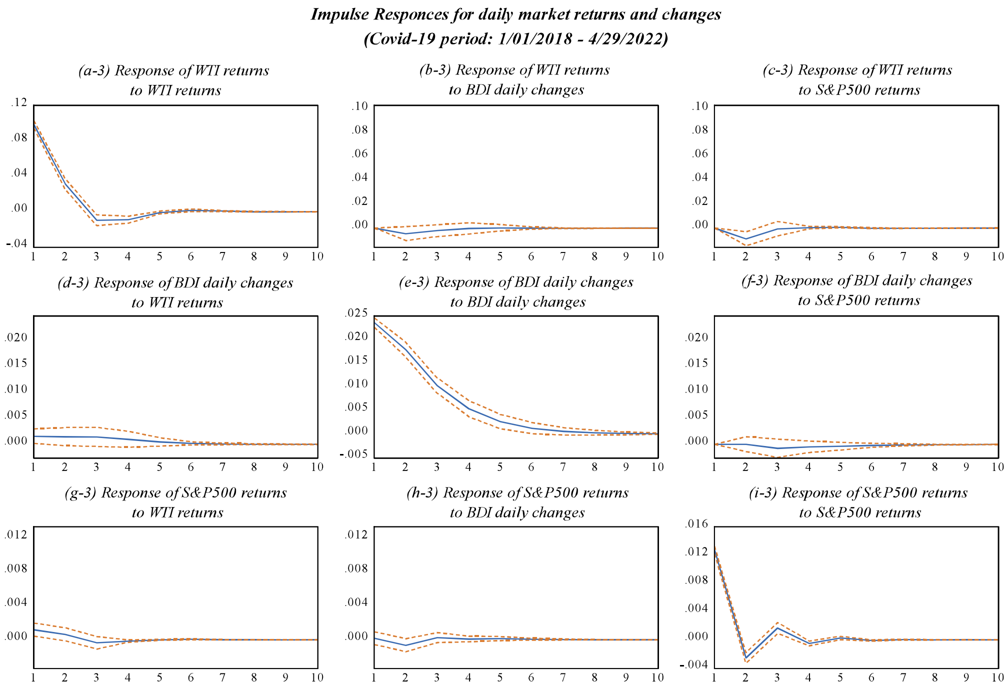


Figure 5 illustrates the waveforms of the shocks estimated using the Impulse Response Function for the period from 2018 to 2022, including the period of the Covid-19 pandemic.

A one standard deviation shock in the WTI return had a positive (0.025%) impact on the WTI return on the same day and then disappeared with a slight but positive (0.0007%) impact again four days later. A one standard deviation shock to the WTI return had no shock effect on the daily change in BDI, while it had a positive effect (0.0005%) on the S&P 500 return one day later and a negative effect (-0.0014%) two days later. The first step in the analysis was to examine the effect of the BDI on the daily change in BDI. Second, a one standard deviation shock in the BDI daily change had a positive effect (0.044%) on the BDI daily change on the same day and disappeared after 10 days. A one-standard-deviation shock to the daily change in BDI had a small positive (0.0001-0.0004%) effect on the WTI return over the 10-day period. Furthermore, a one standard deviation shock in the BDI daily change had a negative impact (-0.001%) on the S&P 500 return after a one-day lag and disappeared after another four-day lag with a positive impact (0.0004%). Finally, a one standard deviation shock in the S&P 500 return had a positive (0.011%) and disappearing effect on the S&P 500 return on the same day. A one standard deviation shock to the S&P 500 return had a negative (-0.0002%) impact on the WTI return on the same day and disappeared with a positive (0.0004%) impact three days later. Furthermore, a one standard deviation shock in the S&P 500 return had a negative (-0.0004%) impact on the daily change in BDI on the same day, and a further negative (-0.0005%) impact that disappeared two days later.

Figure – 5　Impulse response on daily markets during 2018-2022.



6. Conclusion

The purpose of this paper was attempting to clarify the linkage and causality between commodity markets, stock markets, and the real economy using VAR modeling and hypothesis testing with Granger causality tests. In addition, an Impulse Response Function was additionally introduced to observe the response of each market to shocks and to explore the predictability of each market.

The estimation results from the VAR model indicate that all markets have statistically significant correlations to their respective markets. The estimates also suggest that (i) one period prior WTI return, two periods prior WTI return, and one period prior S&P 500 return have an impact on WTI return. (ii) In particular, the BDI daily change one period prior is suggested to have a strong influence on the BDI daily change. (iii) The S&P 500 return of one period prior is implied to have the most influence on the S&P 500 return. However, none of the estimates are notably high, and while each market cannot be said to be uncorrelated to the other, it is difficult to conclude that there is a clear correlation.

Second, the results of hypothesis testing with the Granger causality test indicate that for the entire period (1990-2022) and for other periods (1996-2000, 2006-2010, 2018-2022), the Granger causality of WTI returns and BDI daily changes and S&P 500 returns was changed depending on period. A few points worth mentioning in these empirical results are, first, that BDI daily changes did not have Granger causality for WTI returns and S&P 500 returns. Second, that it is not observed that the reciprocal relationship between commodity markets and the real economy noted by Goldstein and Yang (2022).

Several factors may be causing this phenomenon, the first of which is assumed the existence of a Confounding factor. As an overview of confounding factors, a particular factor influences all the analyzed items, and unless this particular factor is adjusted for, only superficial causality is likely to be detected rather than pure causality. it is considered that this is a quite thorny problem on empirical analysis of causality. The second is the stock market. The S&P 500 was targeted as the empirical modeling for this paper, but since this is an index of the U.S. stock market and not of the world economy, it could be strongly linked to WTI futures, which is also a benchmark for the U.S. oil market. Therefore, it can be inferred that the linkage and causality with BDI would be weak. Thus, future research issues include adjustment for confounding factors and appropriate sample selection.

Finally, in the response of each market to shocks by Impulse Response Function, it is observed that the response of each market to shocks was observed, but extremely weak. However, one characteristic point regarding the waveform of shocks is that the reaction of WTI returns and S&P 500 returns to shocks converged in about one day, while the BDI daily changes took about 10 days to converge. This suggests that the stock and commodity markets have high market liquidity, while the trade market is not as liquid. Unfortunately, when considered in conjunction with the two issues mentioned earlier, confounding factors and sample selection, it is difficult to assert that these results provide predictability for each market.

In concluding this paper, Studies pointing to the linkages with financial markets, including stock markets, in the financialization and financialization of commodity markets (see Tang and Xiong (2012), Silvennoinen and Thorp (2013) and Cheng and Xiong (2014)) and the real economy and commodity markets are considered to be closely related, there is significance in research on the linkage of the three markets, and there is much room for exploration. This paper will hopefully help in this regard.

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Appendix

Table 4. Summary of Lag length criteria

Lag	AIC	SC	HQ
0	-14.6111	-14.60864	-14.6103
1	-15.4171	-15.40703	-15.4136
2	-15.4508	-15.43327*	-15.4448
3	-15.4564	-15.43135	-15.4479
4	-15.4598	-15.42722	-15.44868*
5	-15.4595	-15.41943	-15.4458
6	-15.4635	-15.41586	-15.4472
7	-15.4655	-15.41032	-15.4466
8	-15.46670*	-15.40404	-15.4453

Notes: Akaike Information Criterion, Schwarz Information Criterion and Hanna-Quinn Information Criterion is denoted as AIC, SC and HQ, respectively. * indicates lag order selected by the criterion. .