Doctor of Philosophy Dissertation

Time Series analyses on the Chinese and International Fossil Fuel Market: An Investigation From the Time-Varying Aspect.

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Preface

Securing energy is an important issue for any country to achieve economic development. For a country to stabilize its energy supply, mitigating the effects of changes in the energy price change is extremely important. Hence, policymakers engaged in securing energy must pay special attention to factors that could destabilize the energy prices. Recently, sudden shocks such as the 2008 financial crisis and the COVID-19 pandemic have caused devastating impacts on energy prices, and it is becoming crucial to learn how such events can influence the energy market.

Decarbonization is another factor that influences energy policy related to securing energy. Since the world's energy supply still relies heavily on fossil fuels, many countries are struggling to reduce the use of fossil fuels. Being the world's largest CO_2 emitting country, China is now trying to cut its coal use and shift towards natural gas, which is known to emit less CO_2 than coal.

For China to continue its economic growth while shifting toward a lower CO_2 emitting energy, it is imperative to understand how the Chinese fossil fuel markets are affected by sudden shocks and how the relationships between coal, crude oil, and natural gas are changing at this critical juncture, where the issue of climate change is becoming increasingly severe. However, to the best of my knowledge, only a few studies have investigated how the Chinese fossil fuel markets are affected by recent shocks such as the financial crisis of 2008 and the COVID-19 pandemic, and how the relationships among the major fossil fuel markets are changing by focusing on the time-varying aspect of fossil fuel time series data. The time-varying aspect captures the effects of time-varying factors on the parameters estimated in the time series models.

Thus, the current dissertation is distinctive in that it examines how the relationships among the fossil fuel time series variables change from a time-varying aspect. Specifically, I use the following time series methods: the time-varying parameter vector autoregression (TVP-VAR), recursive cointegration test, and Bayesian dynamic conditional correlation-multivariate generalized autoregressive conditional heteroskedasticity (DCC-MGARCH).

First, the TVP-VAR model enables us to capture the potential time-varying nature of the underlying structure in the economy flexibly and robustly based on the Bayesian algorithm method, which can resolve the question of whether the estimated time-varying coefficients are likely to be biased because a possible variation in the volatility of disturbances is ignored. Second, the recursive cointegration test overcomes the short-run parameters as fixed to evaluate the time paths of the non-zero eigenvalues instead of all parameters in the VAR model, which is important for understanding the long-term relationships over time. Third, the Bayesian DCC-MGARCH is a flexible tool for forecasting and capturing the volatility of time series when the volatility varies over time, which is important to have knowledge about volatility because it is a measure of risk. Hence, these methods can decompose time series data into dynamic scales by estimating parameters or volatility over time, which contain more information on the time series under different periods. However, they are yet to be applied to fossil fuel markets.

Thus, this study fills this gap in the literature, and this study aims to test the effectiveness of these time-series methods with time-varying parameters for the fossil fuel market and to examine the time-varying issues related to the fossil fuel market to understand fossil fuel price instability issues. Because fossil fuel markets are often strongly affected by changes in financial markets such as foreign exchange, relevant stock and gold markets, etc., and hedging across the financial markets is crucial for achieving sustainable energy supply, this issue is crucial for institutions seeking to assure energy for their citizens.

For this purpose, Chinese and international fossil fuel markets (coal, crude oil, natural gas, and liquid natural gas (LNG)), foreign exchange markets, clean energy stock markets, gold, and bitcoin markets were selected because of the financialization of fossil fuel commodities, and traders and investors now only consider the fossil fuel market to understand the price stability issue for energy supply is not sustainable; it is necessary to consider the influence of the financial market as a potential diversifier of portfolio risk exposure when changing policies such as the 2005 China exchange rate reform and economic events such as the 2008 financial crisis. The specific research contents are explained as follows:

This dissertation is divided into four parts. This dissertation provides important implications for energy policymakers in stabilizing Chinese and international fossil fuel markets. In addition, this study will help Chinese and international energy investors understand the relationship between the Chinese and international fossil fuel markets and to conduct risk management from a time-varying perspective.

In the first part of this dissertation, I tested the validity of applying the TVP-VAR method to fossil fuel market data to identify the impact of the Chinese Yuan (CNY) and Japanese Yen (JPY) on Chinese LNG import prices. TVP-VAR is known to be useful for identifying how the effect of one time series variable lasts on the other time-series variable. Furthermore, the TVP-VAR model enables us to capture the potential time-varying nature of the time series by estimating the parameter with stochastic volatility (Nakajima, 2011).

Given the 2005 China exchange rate reform and 2013 China's new energy policy to switch from coal to imported natural gas, exchange rate fluctuations could affect imported LNG prices. Moreover, there is no trading market based on supply and demand, and the imported natural gas prices in Asia are linked to Japanese crude oil; therefore, Asian prices are higher than in other regions such as the United States and Europe. Thus, it is necessary to study the issue of how the exchange rate affects the Chinese imported LNG market to understand the natural gas price instability issues.

The empirical study suggests that since September 2005, the JPY pass-through rate on the Chinese LNG import price has been decreasing, while that of the CNY has been increasing. Notably, the pass-through rate of the CNY began to exceed that of the JPY after 2008. Moreover, since 2005, the lag effect of the CNY on the Chinese LNG import price has increased compared to the JPY. If any new currency reform of the CNY is implemented in the future, then the impact of the JPY on the Chinese LNG import price could be reduced and the lag effect of the CNY on the Chinese LNG import price could become longer. Therefore, fluctuations in CNY are becoming an important factor in understanding the movements of Chinese LNG import prices. This implies the significance of considering the effect of the exchange rate on the energy market when the market is influenced by the monetary reform of the importing country.

In the second part of the dissertation, I applied the recursive cointegration test to analyze the connection between the energy market data, given the form of estimating parameters recursively. The recursive cointegration test is known to be effective in identifying the change in the cointegration relationship between two time series variables in the energy market under structural break effects. It is a useful method for investigating how the long-run relationships among the time-series variables change over time.

The Chinese coal market, which accounts for 70% of China's energy consumption, also faces the same stability issues as the imported natural gas market. Thus, it is considered insufficient to understand the problem of price instability from the fossil fuel market of China alone because China’s domestic coal supply depends on the international market. To this end, it is important to study how the Chinese domestic coal market is related to international fossil fuel markets to provide useful information for conducting policies to stabilize coal prices.

Therefore, I applied the recursive cointegration test to recognize the dynamic cointegration relationship between Chinese domestic coal and international fossil fuel markets during 2000–2020, considering the structural break effects due to the 2008 financial crisis. I found that the cointegration relationship between Chinese coal prices and international coal, natural gas, and crude oil prices have different trends before and after 2008. We also found that the Chinese domestic coal price was only cointegrated with the prices of international natural gas prices after 2018. These results indicate that the dynamic cointegration relationships between Chinese domestic coal and international fossil fuel markets change within the investigated period. Natural gas is one of the major energy sources following the 13th Five-Year Plan of China. The stakeholders and policymakers of the Chinese coal market must consider the impact of international natural gas prices to identify Chinese coal price movements to generate more accurate expectations.

In the third part of the dissertation, I employed both the recursive cointegration test and the VAR and VECM models to analyze the shocks in the Chinese and international fossil fuel time series data. A dummy variable capturing the shock in the time-series data is incorporated into the VAR and VECM models to test the impact of the shock on the time-series variables.

Focusing only on one Chinese fossil fuel market (LNG import market or coal market) in the above two research contents is not enough to deeply understand the stability issues of Chinese fossil fuels. Furthermore, the world is affected by the COVID-2019 pandemic crisis. To gain a deeper understanding of the impact of the pandemic crisis on their relationship, it is also important to consider the 2008 financial shock to study the time-varying relationship between China and international fossil fuels from 2000 to 2020.

To determine the validity of identifying shocks for the energy markets, I examined how the dynamic cointegration relationship between the Chinese and international fossil markets changed during the 2008 financial crisis and the COVID-19 pandemic. The results suggest that the effects of COVID-19 on the linkages between the Chinese and international fossil fuel markets are not as evident as in the 2008 financial crisis. The study identifies that the effects of the 2008 financial crisis and the COVID-19 pandemic on the linkages are mostly driven by the impacts of these crises on Chinese fossil fuel markets. This study indicates the importance of controlling the risk involved in the Chinese fossil fuel market when events such as the 2008 financial crisis and the COVID-19 pandemic are changing the linkages between the Chinese and international fossil fuel markets.

In the fourth part of this dissertation, I investigated how the DCC-MGARCH method can be applied to fossil fuels and their hedging market data. The DCC-MGARCH is known to be effective for separating the dynamic correlation relationships among multiple time series variables. This model captures the correlation clustering and examines how a shock at time $t-1$ impacts the correlation at time t.

Hedging between fossil fuels and other assets is important to assure capital for purchasing fossil fuels, which will help stabilize the energy supply. However, events such as the pandemic could make it difficult for the suppliers of energy to hedge the risk of changes in the fossil fuel price by combining their portfolios with financial assets, such as gold and Bitcoin. Thus, it is necessary to consider hedging markets such as clean energy stock, gold, and the Bitcoin market for cross-market investors to understand portfolio risk management based on modern portfolio theory.

To examine its applications on fossil fuel and its hedging markets, the fourth section examines how the dynamic correlation relationship between the fossil fuel and clean energy stock,

gold, and bitcoin market changes after the COVID-19 pandemic took place. The parameters are estimated by the Bayesian method using the US daily data from January 2, 2019, to February 26, 2021, which is divided into periods before and after 2020. The study identifies that the Bayesian DCC-MGARCH model with the skew multivariate generalized error distribution is credible for applying the model for the fossil fuel, clean energy stock, gold, and bitcoin markets to estimate the time-varying conditional correlations between them. The results suggest that the relationships between fossil fuels and the clean energy stock, gold, and bitcoin market are changing and that they become positively correlated after the pandemic occurred. The study indicated the importance of fostering energy and financial market stability and choosing optimal hedging strategies to minimize the diversification of risk when markets are facing shocks such as the COVID-19 pandemic.

This dissertation suggests that the three time-series models are suitable for analyzing fossil fuel market relationships when they are affected by time-varying factors. This empirical dissertation also suggests that the linkage between the energy time series variable data is influenced from changes in energy and monetary policies and exogenous shocks like the financial and COVID-19 crises.

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Part 1: A Study on the Pass-Through Rate of the Exchange Rate on the Liquid Natural Gas (LNG) Import Price in China

1.1 Introduction

North America, West Europe, and Asia-Pacific are the main markets for natural gas consumption in the world but in all of these regions, the liquid natural gas (LNG) import price has been unstable. For example, according to British Petroleum (BP) (2014, 2015), the Japanese LNG import price in Asia-Pacific regions decreased 57.5% from $16.33 to $6.94, the US Natural gas import price declined 43.33% from $4.35 to $2.46, and the UK Heren NBP Index of natural gas import price depreciated 43.15% from $8.25 to $4.69 during 2014–2016. Comparing the changes in the LNG import prices among Japan, the US, and the UK, it is noticeable in this example that the Japanese LNG import price is higher compared to the US and UK markets. The Japanese LNG price and the LNG import price in the Asian area have been fluctuating greatly at a higher price level (ANREME, 2015).

One reason why the Asian LNG price has been higher than other regions is that the Asian LNG import price is known to be related to the average price of Japanese CIF (Cost, Insurance, and Freight) crude oil import price (ANREME 2016). The CIF crude oil has been kept at a higher price to protect sellers and buyers involved in the crude oil trade (Kawamoto and Tsuzaki 2007), and as the international crude oil price increases, the CIF price increases accordingly, making the LNG import price higher. Furthermore, the Asian LNG import price has been much higher than that of Western countries due to the Asian premium, which is a premium imposed on Asian countries' LNG imports from the major gas producers. From the perspective of price stability, it is necessary to reconstruct a different pricing mechanism from the conventional one, which reflects the supply-demand balance on the Asian LNG import price. This is crucial for the Asian natural gas markets to attract market participants (Tong et al. 2014; Choi and Heo, 2017). However, little is known about how the market mechanism functions in determining LNG import prices in the Asian region.

With the development of the Chinese economy, the demand for energy (especially natural gas) has increased dramatically. Since 1978, environmental problems such as PM 2.5 have intensified in China. To cope with such environmental problems, the Chinese government, proposed by the National Development and Reform Commission, announced a decision to change the supply and demand structure from fossil fuels to green energy between 2016–2020 (National Energy Board (NEB) 2016) under the Paris agreement on 3 September 2016. However, according to British Petroleum (BP) (2019), the Chinese consumption of natural gas increased substantially from 81.9 in 2008 to 283 billion cubic meters in 2018, and the Chinese domestic production of natural gas increased from 80.9 to 161.5 billion cubic meters between 2008 and 2018.

Furthermore, factors such as the risk of drastic changes in foreign exchange rates will affect the development of East Asian benchmark prices for the LNG spot market (Shi and Hari 2016). The above-mentioned Asian premium issue and the risks from the foreign exchange rate changes are likely to become more serious as China continues to enhance more LNG imports through the spot market in the future. To address this situation, it is necessary to stabilize LNG import prices. Additionally, the Chinese government should re-examine factors such as foreign exchange risks that play an important role in determining the LNG import benchmark prices. This is crucial since the LNG import benchmark price reflects the supply-demand balance in a real-time way, and it is influential for ensuring the economic efficiency and stability of a natural gas supply. Furthermore, stabilizing the LNG import price in China is imperative for establishing a stable benchmark price and improving its energy security and pricing power for natural gas in the Asia-Pacific markets (Tong et al. 2014).

Another aspect we need to be aware of when investigating the effects of the exchange rate on the Chinese LNG import price is the Chinese Yuan's (CNY) monetary reform. Since July 2005, China has made changes to the CNY exchange rate against the US dollar. However, when China began to apply this monetary reform in 2005, the daily fluctuation of CNY against the US dollar became less than 0.3%. According to the International Monetary Fund (IMF), until 2015, China had a crawling-peg arrangement for its exchange rate regime. On 11 August 2015, the People's Bank of China (PBC) took a decisive step towards floating the CNY. With China's large economic scale and the increasing use of the CNY, the CNY was included in the Special Drawing Right (SDR) basket of the International Monetary Fund (IMF) in 2016. Thus, from November 2016, China introduced a monetary system to peg the CNY against the basket of currencies. Liu and Chen (2017) reported that a more flexible exchange rate regime will bring about a stronger transmission effect from the exchange rate and can cause inflation in China. Since the 2016 monetary reform, there is a debate about whether changes in the CNY's value have effects on the prices of imported goods.

However, up until now, no studies have investigated the exchange rate pass-through of CNY on the Chinese LNG import price considering the effects of CNY monetary reform. To bridge this gap, this study identifies the level of the pass-through rate of the exchange rate on LNG import price. The exchange-rate pass-through refers to the ratio of the price of traded goods that changes with the exchange rate (John et al. 1992).

This research has the following two objectives. First, the study analyzes how the CNY and JPY influence the Chinese LNG import price. The import price of LNG in China is linked with the Japan Crude Cocktail (JCC) price (Martono and Aruga 2018), and the import benchmark price of LNG is likely connected to the Japanese Yen (JPY). Hence, the study considers the effects of the foreign exchange risk on the Chinese LNG import price by comparing the influences on the LNG import price between CNY and JPY. Second, we examine the levels and the length of the pass-through rate of these currencies on the Chinese LNG import price. We do this because it is still not clear to what extent the exchange rate fluctuations influence the Chinese LNG import prices compared to JPY after the 2005 CNY monetary reform.

We expect that before the monetary reform, JPY will have more influence on the LNG price compared to CNY, but this effect will become smaller after the 2005 monetary reform. This is because a study finds that countries with higher exchange rate volatilities have higher pass-through elasticities on import prices (Jose and Linda 2006) and it is known that the volatility of JPY has been higher compared to CNY before 2005. It is also believed that the pass-through rate of JPY on LNG import price will become smaller and shorter after the monetary reform, while that of the CNY will become larger and longer. We expect this result since as the volatility of the CNY increases, the exchange rate risk in the LNG trading market has been gradually transferred to the CNY after 2005, and the effects from the CNY will become more significant in the Chinese LNG market.

The contributions of the present paper are the following. First, from the perspective of discovering the Chinese LNG import price, suppliers in the international LNG market need to consider the impact of exchange rate fluctuations on the Chinese LNG import price. Therefore, the results of this study provide valuable price discovery information for the international LNG suppliers exporting LNG to China. Second, the paper could be a good reference to energy-consuming countries that need to mitigate the effects of exchange rate changes on energy prices. As China is a country whose exchange rate rule is changing rapidly, the current study could be a useful source for understanding the impact of monetary reform on energy markets. Finally, this is one of the first studies to apply the Time-Varying Parameter vector autoregressive (TVP-VAR) model on an energy market to consider the effects of dynamic changes in the estimated parameters. Application of the TVP-VAR model is becoming popular in monetary and economic studies, but this method has not been used often for analyzing the dynamics of energy markets. Hence, the study can help scholars involved in analyzing energy markets with dynamic changes to understand the effectiveness of applying the TVP-VAR model on energy market data.

1.2 Previous Studies

Many studies have analyzed the pass-through rate of exchange rate on the import and export commodity prices. Some studies concluded that exchange rates have an incomplete pass-through on import commodity prices (Shinkai 2011; Choudhria and Hakura 2015; Pennings

2017) but Choudhria and Hakura (2015) showed that the pass-through from the exchange rate to import and export goods are different. They revealed that there is an incomplete pass-through from the exchange rate to import goods but there is a significant pass-through on the export goods. Pennings (2017) indicated that the pass-through is incomplete for producer prices. Furthermore, Kurtović et al. (2018) found that the pass-through rate on import and export goods are asymmetric in the cases of monetary appreciation and depreciation.

Moreover, according to Ceglowski (2010), in addition to oil prices, most of the pass-through rate on the US import goods dropped sharply from 1992 to 2006 (Sekine 2006), and the same conclusion was reported in Japan after 1970 (Sekine 2006; Shioji and Uchino 2009). Shinkai (2011) found that the pass-through rate on import price increases when exchange rate volatility increases in the short run, but this trend is associated with inflation in the long run. Sasaki (2019) found that Japan's import pass-through rate had been declining, but it started to increase during the financial crisis. On the other hand, Kurtović et al. (2018) reported that there has been no decrease in the pass-through rates on the aggregate import prices of 7 Southeast European countries. Hui et al. (2013) reported that compared to developed countries, developing countries have a higher pass-through rate. Thus, it is likely that the pass-through rate on the Chinese LNG import price will be high, but up until now, no studies have confirmed the extent of the pass-through rate on the Chinese LNG import price.

We would also like to introduce studies related to the recent development of the methods used for analyzing the pass-through rate on import prices. Conventionally, the Vector autoregression (VAR) model has been applied for investigating the pass-through rate on commodity prices (Marazzi et al. 2005; Shinkai 2011). However, recently, according to the idea that the economic structure and conditions of financial policy change over time, the pass-through rate on import commodity prices was analyzed by considering the effects of changes in the estimated parameters over time (Sasaki 2019). For example, Primiceri (2005) applied the time-varying parameter VAR (TVP-VAR) model to investigate the effects of changes in the US monetary policy in the 1970s and early 1980s. Nakajima and Watanabe (2012) developed the TVP-VAR extrapolation program in OX software using the macro data of Japan. They suggested that compared to VAR model fixing parameters, TVP-VAR considering time-varying parameters improves the accuracy of the prediction of any variable (Nakajima and Watanabe 2012). Studies such as Shioji and Uchino (2009) and Shioji (2010) also measured the pass-through rate of the exchange rate on various commodities using the TVP-VAR.

Finally, there are a lot of concerns about how the fluctuations of the CNY will influence the Chinese economy, production, and import and export prices over time. However, there is no study investigating how the Chinese LNG import price has been and will be affected by the

CNY and JPY fluctuations in the aftermath of China's currency reform process. To cover this gap, this study examines the influence of the JPY and CNY on the Chinese LNG import price and compares the pass-through rate of these currencies on the Chinese LNG import price using the latest data available.

Our study is also novel in the sense that although most previous studies analyzed the pass-through rate by using the VAR model, the current study uses the TVP-VAR model to estimate the effects of the monetary rates on the Chinese LNG import price. This model enables us to consider the effects of dynamic changes in the estimated parameters.

1.3 Materials and Methods

The pass-through rate of the exchange rate on the Chinese LNG import price was estimated using four variables: the CNY ($\mathrm{E1}_t$), JPY ($\mathrm{E2}_t$), Chinese LNG import price (PL_t), and Japanese crude oil price (PJ_t). Since Asian LNG import price is linked with the JCC crude oil price (Martono and Aruga 2018) and causes major impacts on the global natural gas industry chain, the Japanese crude oil price was included in the study.

Our econometric model was based on Primiceri's TVP-VAR model (Nakajima and Watanabe 2012), which incorporates the effects of changes in the parameters during the test period. The model was estimated by using the Monte Carlo experiment with the OX 6 Console. Before estimating the TVP-VAR model, we tested the stationarity of our test variables with unit root tests. Then, we tested the cointegration between our variables to see if the VAR model was a suitable model for applying the data.

1.3.1 Unit Root and Cointegration Test Method

To identify the stationarity of our test variables, we applied the Augmented Dickey-Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The ADF and PP test the non-stationarity of the variables while the KPSS tests the stationarity of the variables.

After the order of integration was confirmed with the unit root tests, we performed the Johansen cointegration tests. The Johansen tests were conducted using the two monetary rates and LNG and crude oil prices: $(\mathrm{E1}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$ and $(\mathrm{E2}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$. Eviews 8.0 software was used for this purpose.

1.3.2 TVR-VAR Model

Based on the assumption that the variables have unit roots and are not cointegrated, the TVP-VAR model has a different structure from the VAR model; the estimated parameters change over time (Primiceri 2005). To consider such parameter changes over time, we applied the TVP-VAR model on the CNY (E1), JPY (E2), Chinese LNG average import price (PL), and JCC average crude oil price. The JCC price was included in our model, which was mainly to avoid the impact of the JCC price on foreign exchange and to better understand the impact of the exchange rate on the Chinese LNG import price. The lag order of the time-varying model was determined by using the minimum AIC value obtained from the VAR model. In this study, two time-varying models for the CNY and JPY were constructed to compare the effects of these exchange rates on the Chinese LNG import price.

In the CNY TVP-VAR model, the Chinese LNG import price (PL), CNY(E1) monetary rate, and the JCC crude oil price (PJ) was set as $Y_{E1,t} = (\mathrm{PL}_t, \mathrm{E1}_t, \mathrm{PJ}_t)'$. The model was constructed as follows:

$$\Delta \mathrm{Y}_{\mathrm{E1,t}} = \mathrm{C}_{\mathrm{E1,t}} + \mathrm{B}_{\mathrm{E1,1t}} \Delta \mathrm{Y}_{\mathrm{E1,t-1}} + \cdots + \mathrm{B}_{\mathrm{E1,st}} \Delta \mathrm{Y}_{\mathrm{E1,t-s}} + \mathrm{u}_{\mathrm{E1,t}}, \tag{1}$$

$$\mathrm{u}_{\mathrm{E1,t}} \sim \mathrm{N}(0, \Omega_{\mathrm{E1,t}}), \mathrm{t} = \mathrm{s} + 1, \ldots, \mathrm{n} \tag{2}$$

where Δ denotes the first difference of the variable.

Similarly, for the JPY model, the three main variables of our interest were set as $Y_{E2,t} = (\mathrm{PL}_t, \mathrm{E2}_t, \mathrm{PJ}_t)'$ and the model had the following form:

$$\Delta \mathrm{Y}_{\mathrm{E2,t}} = \mathrm{C}_{\mathrm{E2,t}} + \mathrm{B}_{\mathrm{E2,1t}} \Delta \mathrm{Y}_{\mathrm{E2,t-1}} + \cdots + \mathrm{B}_{\mathrm{E2,st}} \Delta \mathrm{Y}_{\mathrm{E2,t-s}} + \mathrm{u}_{\mathrm{E2,t}}, \tag{3}$$

$$\mathrm{u}_{\mathrm{E2,t}} \sim \mathrm{N}(0, \Omega_{\mathrm{E2,t}}), \quad \mathrm{t} = \mathrm{s} + 1, \ldots, \mathrm{n}. \tag{4}$$

Here, $C_{E1,t} = (c_{\mathrm{PL,E1t}}, c_{\mathrm{E1t}}, c_{\mathrm{PJ,E1t}})', C_{E2,t} = (c_{\mathrm{PL},E2\mathrm{t}}, c_{E2\mathrm{t}}, c_{\mathrm{PJ},E2\mathrm{t}})'$ are the time-varying constant vectors of (3 × 1), $B_{E1,it}, B_{E2,it}$ are the time-varying coefficient matrices ($i = 1, \ldots, \mathrm{s}$) of (3 × 3), and $u_{E1,t} = (u_{\mathrm{PL,E1t}}, u_{\mathrm{E1t}}, u_{\mathrm{PJ,E1t}})', u_{E2,t} = (u_{\mathrm{PL},E2\mathrm{t}}, u_{E2\mathrm{t}}, u_{\mathrm{PJ},E2\mathrm{t}})'$ are error term vectors of (3 × 1).

The error terms $u_{E1,t}, u_{E2,t}$ in Equations (2) and (4) were assumed to follow the variate normal distribution with an average of 0 and time-varying covariance matrices of $\Omega_{E1,t}$. The time-varying covariance matrices $\Omega_{E1,t}, \Omega_{E1,t}$ were expanded by using the Cholesky decomposition:

$$\Omega_{\mathrm{E1,t}} = \mathrm{A}_{\mathrm{E1,t}}^{-1} \Sigma_{\mathrm{E1,t}} \Sigma_{\mathrm{E1,t}}' \mathrm{A}_{\mathrm{E1,t}}^{-1}{}', \tag{5}$$

$$\Omega_{\mathrm{E2,t}} = \mathrm{A}_{\mathrm{E2,t}}^{-1} \Sigma_{\mathrm{E2,t}} \Sigma_{\mathrm{E2,t}}' \mathrm{A}_{\mathrm{E2,t}}^{-1}{}', \tag{6}$$

where $A_{E1,t}, A_{E2,t}$ are diagonal matrices of (3). Here, all the diagonal components were

$$A_{E1,t} = \begin{pmatrix} 1 & 0 & 0 \\ a_{E1,21t} & 1 & 0 \\ a_{E1,31t} & a_{E1,32t} & 1 \end{pmatrix}, A_{E2,t} = \begin{pmatrix} 1 & 0 & 0 \\ a_{E2,21t} & 1 & 0 \\ a_{E2,31t} & a_{E2,32t} & 1 \end{pmatrix}.$$

In addition, $\Sigma_{\mathrm{E1,t}}, \Sigma_{\mathrm{E2,t}}$ were the diagonal matrices of (3 × 3) where

$$\Sigma_{E1,t} = \begin{pmatrix} \sigma_{E1,1t} & 0 & 0 \\ 0 & \sigma_{E1,2t} & 0 \\ 0 & 0 & \sigma_{E1,3t} \end{pmatrix}, \Sigma_{E2,t} = \begin{pmatrix} \sigma_{E2,1t} & 0 & 0 \\ 0 & \sigma_{E2,2t} & 0 \\ 0 & 0 & \sigma_{E2,3t} \end{pmatrix}.$$

Here, $\sigma_{E1,it}^2, \sigma_{E2,it}^2$ were the time-varying variances of structural shocks for variable i, while $a_{E1,ijt}$ and $a_{E2,ijt}$ were the parameters of the time-varying simultaneous correlations given to the variable i by the structural shock of the variables j where $(i, j = 1,2,3)$.

Then, based on Equations (1), (2), and (5), the CNY(E1) model could be rewritten as the following equations:

$$\Delta Y_{E1,t} = \Delta X'_{E1,t}\beta_{E1,t} + A_{E1,t}^{-1}\Sigma_{E1,t}\varepsilon_{E1,t}, \tag{7}$$

$$\varepsilon_{E1t} \sim N(0, I_3). \tag{8}$$

Similarly, based on Equations (3), (4), and (6), the JPY (E2) model could be expressed as follows:

$$\Delta Y_{E2,t} = \Delta X'_{E2,t}\beta_{E2,t} + A_{E2,t}^{-1}\Sigma_{E2,t}\varepsilon_{E2,t}, \tag{9}$$

$$\varepsilon_{E2,t} \sim N(0, I_3). \tag{10}$$

Here, $\beta_{E1,t}, \beta_{E2,t}$ were the vectors corresponding to Equations (7) and (9):

$$\beta_{E1,t} = \{C_{E1,t}, B_{E1,1t}, \dots, B_{E1,st}\}, \beta_{E2,t} = \{C_{E2,t}, B_{E2,1t}, \dots, B_{E2,st}\}.$$

$\Delta X'_{E1,t}$ is defined as below:

$$\Delta X'_{E1,t} = I_3 \otimes (1, \Delta Y'_{E1,t-1}, \dots, \Delta Y'_{E1,t-s}), \Delta X'_{E2,t} = I_3 \otimes (1, \Delta Y'_{E2,t-1}, \dots, \Delta Y'_{E2,t-s}),$$

where I_3 is the identity matrix of 3×3, and $\otimes$ is the Kronecker product. In addition, $\varepsilon_{E1,t} = (\varepsilon_{E1,1t}, \varepsilon_{E1,2t}, \varepsilon_{E1,3t})', \varepsilon_{E2,t} = (\varepsilon_{E2,1t}, \varepsilon_{E2,2t}, \varepsilon_{E2,3t})'$ in Equations (8) and (10) are the normalized structural shocks.

The time-varying parameter was set by assuming the following equations:

$$\beta_{E1,t+1} = \beta_{E1,t} + \delta_{E1,\beta t}, \ \beta_{E2,t+1} = \beta_{E2,t} + \delta_{E2,\beta t}, \tag{11}$$

$$\alpha_{E1,t+1} = \alpha_{E1,t} + \delta_{E1,\alpha t}, \ \alpha_{E2,t+1} = \alpha_{E2,t} + \delta_{E2,\alpha t}, \tag{12}$$

$$h_{E1,t+1} = h_{E1,t} + \delta_{E1,ht}, \ h_{E2,t+1} = h_{E2,t} + \delta_{E2,ht}, \tag{13}$$

where,

$$\begin{pmatrix} \varepsilon_{E1,t} \\ \delta_{E1,\beta t} \\ \delta_{E1\alpha t} \\ \delta_{E1ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I_3 & O & O & O \\ O & \Sigma_{E1,\beta} & O & O \\ O & O & \Sigma_{E1,\alpha} & O \\ O & O & O & \Sigma_{E1,h} \end{pmatrix}\right) \text{ and}$$

$$\begin{pmatrix} \varepsilon_{E2,t} \\ \delta_{E2,\beta t} \\ \delta_{E2\alpha t} \\ \delta_{E2ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I_3 & O & O & O \\ O & \Sigma_{E2,\beta} & O & O \\ O & O & \Sigma_{E2,\alpha} & O \\ O & O & O & \Sigma_{E2,h} \end{pmatrix}\right).$$

$\alpha_{E1,t} = (a_{E1,21t}, a_{E1,31t}, a_{E1,32t})'$ *and* $\alpha_{E2,t} = (a_{E2,21t}, a_{E2,31t}, a_{E2,32t})'$ are the lower triangular components of the $A_{E1,t}$ *and* $A_{E2,t}$ matrices. The diagonal components $\Sigma_{E1,t}$ *and* $\Sigma_{E2,t}$ were converted into $h_{E1,it} = \log \sigma^2_{E1,it}$ *and* $h_{E2,it} = \log \sigma^2_{E2,it}$ $(i = 1,2,3)$ where $h_{E1,t} = (h_{E1,1t}, h_{E1,2t}, h_{E1,3t})'$ *and* $h_{E2,t} = (h_{E2,1t}, h_{E2,2t}, h_{E2,3t})'$. The time-varying parameters for the CNY and JPY models were defined as $(\beta_{E1,t}, \alpha_{E1,t}, h_{E1,t})$ *and* $(\beta_{E2,t}, \alpha_{E2,t}, h_{E2,t})$.

The prior distributions corresponding to $(\Sigma_{E1,\beta}, \Sigma_{E1,\alpha}, \Sigma_{E1,\mathrm{h}})$ and $(\Sigma_{E2,\beta}, \Sigma_{E2,\alpha}, \Sigma_{E2,\mathrm{h}})$ were set as follows:

$$\Sigma_{E1,\beta} \sim IW(n_{E1,0}, S_{E1,0}), \Sigma_{E1,\alpha} \sim IG(v_{E1,\alpha 0}/2, V_{E1,\alpha}/2), \Sigma_{E1,h} \sim IG(v_{E1,h0}/2, V_{E1,h}/2), \quad (14)$$

$$\Sigma_{E2,\beta} \sim IW(n_{E2,0}, S_{E2,0}), \Sigma_{E2,\alpha} \sim IG(v_{E2,\alpha 0}/2, V_{E2,\alpha}/2), \Sigma_{E2,h} \sim IG(v_{E2,h0}/2, V_{E2,h}/2). \quad (15)$$

In Equations (14) and (15), the IW and IG denote the Inverse Wishart and Inverse Gamma distributions, respectively.

In this study, the above time-varying parameter $(\beta_{et}, \alpha_{et}, \mathrm{h}_{et})$ where $e = (E1, E2)$ in the TVP-VAR model was estimated using Bayesian theory. The Markov chain Monte Carlo (MCMC) method in the framework of Bayesian Inference was used for estimating the time-varying parameters. According to Nakajima and Watanabe (2012), $Y = \{Y_{et}\}_{t=1}^{n}, \beta = \{\beta_{et}\}_{t=s+1}^{n}, \alpha = \{\alpha_{et}\}_{t=s+1}^{n}, h = \{h_{et}\}_{t=s+1}^{n}$, and $\omega = (\Sigma_{e,\beta}, \Sigma_{e,\alpha}, \Sigma_{e,h})$. Table 1.1 illustrates the sampling steps using the joint posterior probability density function $\pi(\beta, \alpha, \mathrm{h}, \omega | Y)$ and the MCMC method. The details of the steps are explained in Nakajima and Watanabe (2012) and Nakajima (2011).

Table 1.1 Sampling steps of the Markov chain Monte Carlo (MCMC) method.

Steps	Detail of Steps
1	Set the initial value of β, α, h, ω.
2	Sampling from $\beta \vert \alpha, h, \Sigma_\beta, Y$.
3	Sampling from $\Sigma_\beta \vert \beta$.
4	Sampling from $\alpha \vert \beta, h, \Sigma_\alpha, Y$.
5	Sampling from $\Sigma_\alpha \vert \alpha$.
6	Sampling from $h \vert \beta, \alpha, \Sigma_h, Y$.
7	Sampling from $\Sigma_h \vert h$.
8	Back to step 2.

In step 1, there is a possibility that the estimated value of the fixed parameter is unstable when the estimation period is short (Nakajima and Watanabe 2012). In this case, the prior distribution of the initial value of the time-varying parameters of the first 10 samples is drawn from the normal distribution as prior data (Primiceri 2005). The mean and covariance matrices of the prior distribution are determined by the ordinary fixed-parameter VAR model (Kosumi

2016). Using the obtained average estimated values ($\hat{\beta}_{e,0}, \hat{\alpha}_{e,0}, \hat{h}_{e,0}$) and the estimated values of the covariance matrix ($V(\hat{\beta}_{e,0}), V(\hat{\alpha}_{e,0}), V(\hat{h}_{e,0})$), the following normal distribution was set:

$$\beta_{e,s+1} \sim N(\hat{\beta}_{e,0}, 4V(\hat{\beta}_{e,0})), \alpha_{e,s+1} \sim N(\hat{\alpha}_{e,0}, 4V(\hat{\alpha}_{e,0})), h_{e,s+1} \sim N\left(\hat{h}_{e,0}, 4V(\hat{h}_{e,0})\right). \quad (16)$$

In the MCMC method, it takes some time for the Markov chain to converge to the target distribution, so the first part of the sample sequence was discarded. The expected value was calculated using the remaining samples, and it was determined whether the chain converged (Kosumi 2016). In this study, the convergence test was performed with the following methods.

First, we examined the convergence by plotting the sample parameters using the MCMC method. We used the plots to find out whether the fluctuation of the sample is stable (Kosumi 2016).

Second, the CD statistic proposed by Geweke (1991) was used. The CD statistic was used to identify whether the averages of the first to last sub-samples are the same. If the test suggested that the sample parameters converge to samples from the posterior distribution, and if the mean difference among the first to last sub-samples extracted became zero, then we could confirm that the parameters did converge.

Finally, the prior distribution was based on Nakajima and Watanabe (2012) and the estimation is completed with the Ox program for the TVP-VAR model provided by Nakajima (2011).

1.3.3 Impulse Response Function

The impulse response method is a way to see how the innovation given to the error term of an equation propagates to the test variables. Since the models for the CNY ($E1_t, PL_t, PJ_t$) and JPY ($E2_t, PL_t, PJ_t$) are constructed in the same way, we only discuss the impulse response function for the CNY ($E1_t, PL_t, PJ_t$).

The TVP-VAR model of Equation (1) with two lags can be rewritten as follows:

$$\Delta Y_{E1,t} = C_{E1,t} + B_{E1,1,t}\Delta Y_{E1,t-1} + B_{E1,2,t}\Delta Y_{E1,t-2} + u_{E1,t}\,. \quad (17)$$

Here, $C_{E1,t} = (c_{PL,E1t}, c_{E1t}, c_{PJ,E1t})'$, is a time-varying constant vector of (3×1), $B_{E1,1t}, B_{E1,2t}$ is a time-varying coefficient matrix of (3×3), and $u_{E1,t} = (u_{PL,E1t}, u_{E1t}, u_{PJ,E1t})'$ is an error term vector of (3×1). The initial value of $\Delta Y_{E1,t}$ was set to zero ($\Delta Y_{E1,0} = 0$).

The impulse response function can be obtained by the following steps. First, let the value of $\Delta Y_{E1,t}$ when innovation is not given ($\Omega_{E1,t} = 0, \forall t$) be $\Delta Y^{n}_{E1,t}$. Second, according to Equation (17), let the value in period $t = 1$ be $\Delta Y^{n}_{E1,1} = C_{E1,1}$ while the next period's value is $\Delta Y^{n}_{E1,2} =$

$C_{E1,2} + B_{E1,2,2}C_{E1,1}$. The value of $\Delta Y_{E1,t}$ when innovation is given ($\Omega_{E1,t} = \sigma_{E1,t}, \forall t$) is denoted as $\Delta Y^{a}_{E1,t}$. Hence, the value of ΔY in period $t = 1$ is $\Delta Y^{a}_{E1,1} = C_{E1,1} + \sigma_{E1,1}$ and the next period's value is $\Delta Y^{a}_{E1,2} = C_{E1,2} + B_{E1,2,2}(C_{E1,1} + \sigma_{E1,1}) + \sigma_{E1,2}$.

Next, by calculating the difference between the case without and with innovations, the effect of innovation can be expressed as $\Delta Y^{d}_{E1,t} = \Delta Y^{a}_{E1,t} - \Delta Y^{n}_{E1,t}$. In this case, ΔY can be expressed as:

$$\Delta Y^{d}_{E1,1} = \sigma_{E1,1}, \Delta Y^{d}_{E1,2} = B_{E1,2,2}\sigma_{E1,1} + \sigma_{E1,2}\,. \tag{18}$$

Equation (18) is called the impulse response function, and the cumulative response function is defined for every lag period (t = 1,2, ...).

Finally, the pass-through rate on the LNG import price is defined as (cumulative impulse response to the foreign exchange shock of the import price)/(cumulative impulse response to the own monetary shock) (Shioji 2010). Based on the cumulative response function, the pass-through rate on the Chinese LNG import price can be expressed as:

$$R^{E1\to PL}_{pass-through} = \frac{T^{D}_{E1\to PL,t}}{T^{D}_{E1\to E1,t}}. \tag{19}$$

Here, $R^{E1\to PL}_{pass-through}$ is the pass-through related to the fluctuation of the CNY on the Chinese LNG import price, and $T^{D}_{E1\to PL,t}$ is the accumulative impulse response of the CNY fluctuation shock on the Chinese LNG import price. Finally, $T^{D}_{E1\to E1,t}$ is the accumulative impulse response to its own shock from the CNY fluctuation. All the impulse response function estimations were performed with OxMetrics6.01.

1.3.4 Data

The monthly average price from China Customs (Wind 2019) was used for the LNG import price. The monthly average price released by the Petroleum Association of Japan (Wind 2019) was used for the JCC crude oil price. Furthermore, the nominal effective exchange rate was the exchange rate used in the study. The CNY fluctuation is the monthly average nominal effective data published by the People's Bank of China and the data were collected from Wind Net. The JPY represents the monthly average nominal effective data released by the Bank of Japan. The sample period covered in this study was from August 2005 to September 2018. All the data used in this study is provided as supplementary material.

Figure 1.1 is the plots of the standardized data of our variables ($E1_t, E2_t, PJ_t, PL_t$) calculated from Equation (20). From this figure, we can see that the CNY ($E1_t$) is more volatile than the JPY (($E2_t$). It is also discernible from the figure that the China LNG import price (PL_t) seems to fluctuate along with the Japanese crude oil price (PJ_t).

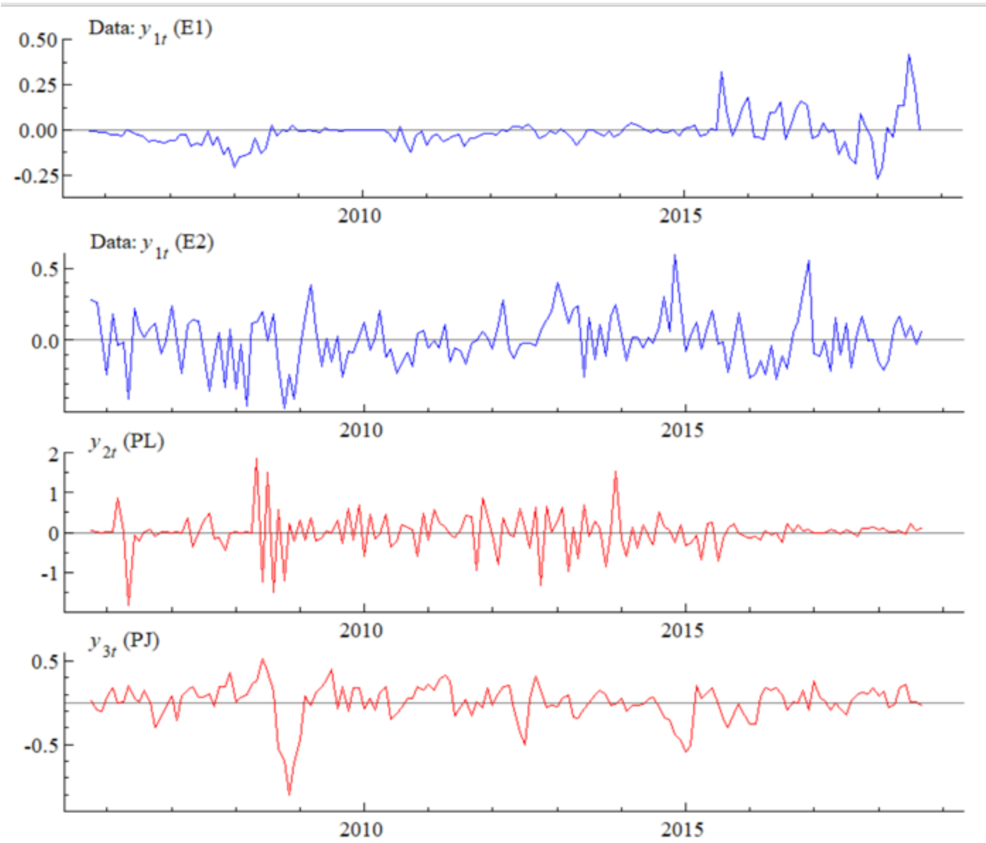


Figure 1.1 The plots of CNY ($\mathrm{E1}_t$), JPY ($\mathrm{E2}_t$), crude oil (PJ_t) and LNG import (PL_t) prices from August 2005 to September 2018.

As US dollars are the most commonly used currency in international trades, we used US dollars as the base unit for our variables. Thus, the JCC crude oil import prices and Chinese LNG import prices were converted to dollar-denominated prices for unifying the Japanese and Chinese markets. However, because the data of the variables have different units, they were standardized by using the following formula:

$$\mathrm{Z} = \frac{\mathrm{X} - \mu}{\sigma}. \tag{20}$$

Here, Z is the normalized value of X where X denotes the variable of our interest (CNY, JPY, JCC crude oil import price, and Chinese LNG import price), while μ and σ are the mean and variance of X.

1.4 Results

1.4.1 Unit Root and Cointegration Tests

Table 1.2 depicts the results of the unit root tests. The table indicates that all our time series data are non-stationary at their level data but become stationary when first differencing them, suggesting that they are all integrated at order one.

Tables 1.3 and 1.4 show the results of the Johansen test for the CNY and JPY versus the natural gas and crude oil prices. The results of the maximum eigenvalue test suggest that both the CNY and JPY are not cointegrated with the natural gas and crude oil prices based on the 5% significance level. These results point out the validity of using the TVP-VAR model instead of the TVP vector error correction model (VECM).

Table 1.2 Unit root tests.

Variables	Level Data (t-Value)			First Difference Data		
	ADF	PP	KPSS	ADF	PP	KPSS
E1	−1.29	−2.43	0.98 *	8.04 *	−6.71 *	0.63
E2	−0.16	−1.34	0.31	3.06 *	−9.68 *	0.18
PL	−0.34	−2.45	0.71 *	−5.85 *	−22.49 *	0.09
PJ	−0.46	−2.19	0.26	8.48 *	−5.58 *	0.07

* Significant at the 5% significance level.

Table 1.3 Results of the Johansen cointegration test for CNY $(\mathrm{E1}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$.

Rank Number	Trace Test Statistic	0.01 Critical Value	p-Value	Maximum Eigenvalue Test Statistic	0.01 Critical Value	p-Value
None	31.38 *	35.46	0.03	16.00	25.86	0.22
At most 1	15.38	19.94	0.05	10.94	18.52	0.15
At most 2	4.44 *	6.63	0.03	4.44 *	6.63	0.03

* Significant at the 5% significance level.

Table 1.4 Results of the Johansen cointegration test for JPY $(\mathrm{E2}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$.

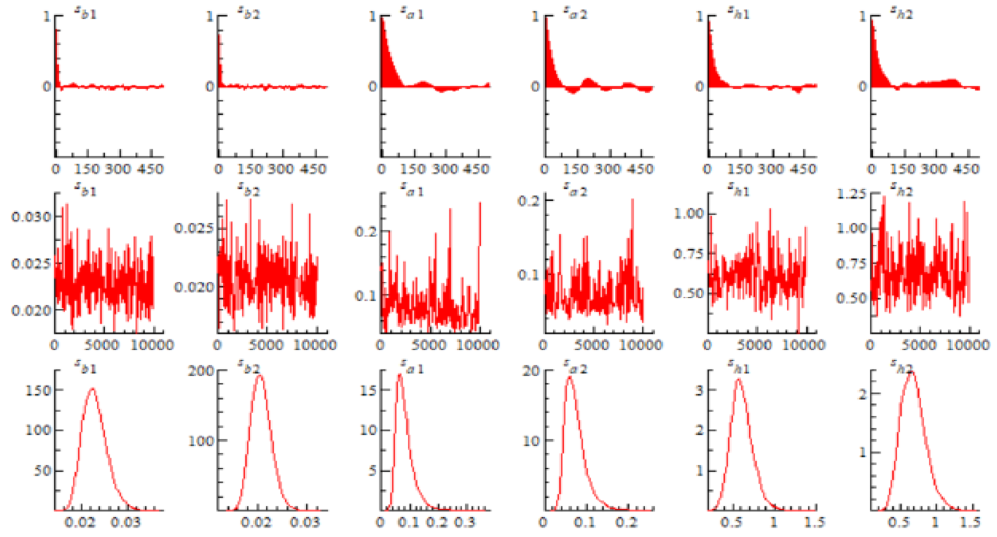
Rank Number	Trace Test Statistic	0.01 Critical Value	p-Value	Maximum Eigenvalue Test Statistic	0.01 Critical Value	p-Value
None	24.02	35.46	0.19	12.04	25.86	0.54
At most 1	11.98	19.94	0.16	7.29	18.52	0.45
At most 2	4.68 *	6.63	0.03	4.68 *	6.63	0.03

* Significant at the 5% significance level.

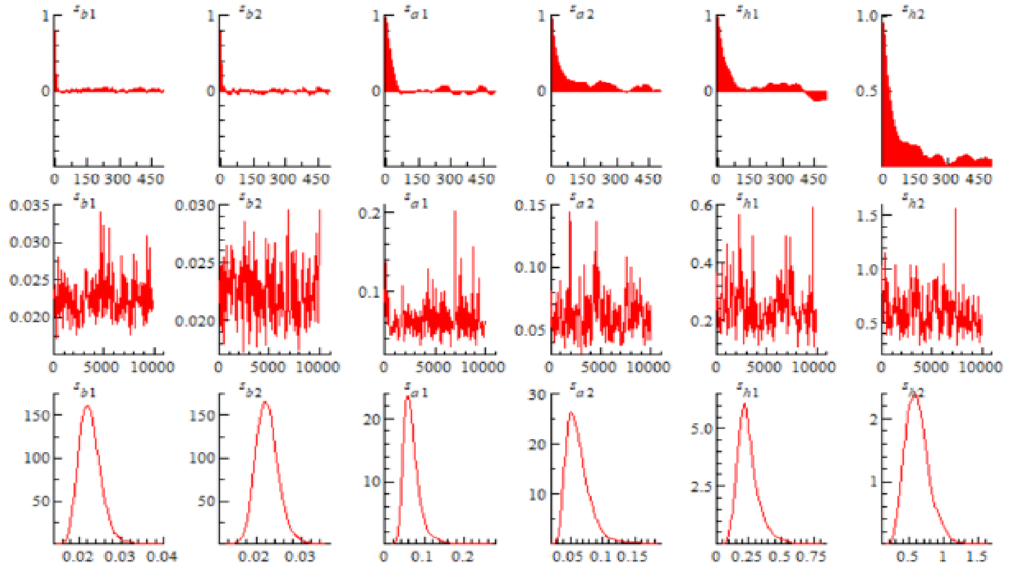
1.4.2 MCMC Estimation Results

In the MCMC estimation, we ran 10,000 iterations with a burn-in phase of 1000, and a thinning interval of 10.

Figures 1.2 is the sample autocorrelation function (upper), sample-path (middle), and posterior probability density function (bottom) of time-varying parameters obtained by the estimation. From the results in Figures 2a,b, both sample paths (middle) converge after 1000 iterations. The sample autocorrelation function shows that both the coefficients (upper) for CNY and JPY were approximately reduced to 0 after 500 iterations. In addition, the results following the normal distribution were obtained for all parameters of the posterior probability density function (bottom).



(a) The CNY $(\mathrm{E1}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$



(b) The JPY $(\mathrm{E2}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$

Figure 1.2 The sample autocorrelation function (upper), sample-path (middle), and posterior probability density function (bottom) of TVP-VAR parameters. $\mathrm{s_{b1}}$, $\mathrm{s_{a1}}$, and $\mathrm{s_{h1}}$ are error terms of the original time-varying parameters based on the first n_0 sub-samples. $\mathrm{s_{b2}}$, $\mathrm{s_{a2}}$, and $\mathrm{s_{h2}}$ are error terms of the original time-varying parameters based on the last n_1 sub-samples. The vertical axis of the upper figure is the sample autocorrelation, and the horizontal axis denotes the number of iterations. The vertical axis of the middle figure is the sample path and the horizontal axis is the number of iterations. The vertical axis of the bottom figure is the posterior probability density and the horizontal axis is the deviation from the average.

Table 1.5 Estimation results of the TVP-VAR model parameters on the CNY $(\mathrm{E1}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$.

Parameter	Average	Standard Deviation	95%Credit Section	CD	Inefficiency Factor
s_{b1}	0.023	0.003	[0.018, 0.029]	0.422 *	9.160
s_{b2}	0.021	0.002	[0.017, 0.025]	0.594 *	6.650
s_{a1}	0.082	0.032	[0.043, 0.163]	0.38 *	70.690
s_{a2}	0.074	0.026	[0.040, 0.140]	0.165 *	51.010
s_{h1}	0.610	0.132	[0.385, 0.901]	0.009 *	41.910
s_{h2}	0.686	0.168	[0.397, 1.063]	0.147 *	56.460

* Significant at the 5% significance level. CD is the normal distribution statistic of Geweke's (1991) convergence test. s_{b1}, s_{a1}, and s_{h1} are error terms of the original time-varying parameters based on the first n_0 sub-samples. s_{b2}, s_{a2}, and s_{h2} are error terms of the original time-varying parameters based on the last n_1 sub-samples.

Table 1.6 Estimation results of the TVP-VAR model parameters on the JPY $(\mathrm{E2}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$.

Parameter	Average	Standard Deviation	95%Credit Section	CD	Inefficiency Factor
s_{b1}	0.023	0.003	[0.018, 0.028]	0.542 *	9.360
s_{b2}	0.022	0.002	[0.018, 0.028]	0.154 *	5.170
s_{a1}	0.068	0.022	[0.039, 0.125]	0.912 *	41.420
s_{a2}	0.063	0.019	[0.038, 0.124]	0.432 *	78.930
s_{h1}	0.246	0.084	[0.124, 0.458]	0.879 *	72.560
s_{h2}	0.613	0.171	[0.331, 1.001]	0.214 *	89.370

* Significant at the 5% significance level. CD is the normal distribution statistic of Geweke's (1991) convergence test. s_{b1}, s_{a1}, and s_{h1} are error terms of the original time-varying parameters based on the first n_0 sub-samples. s_{b2}, s_{a2}, and s_{h2} are error terms of the original time-varying parameters based on the last n_1 sub-samples.

Tables 1.5 and 1.6 show the posterior mean, standard deviation, 95% confidence interval, Geweke's convergence decision (CD) statistic (p-value) (Geweke 1991), and the inefficiency factor of the two-sided parameters for the CNY and JPY. Instead of looking directly at the sample path, we used the CD statistics to estimate how many samples were needed to obtain the same variance as the sample mean, which was calculated from the uncorrelated samples. This is called the inefficiency factor. The value of the CD statistics suggests that the model parameters converged to the posterior distribution. As explained before, the CD statistic is the normal distribution statistic of Geweke (1991) for the convergence test and it is known that the Z value of the normal test statistic is 1.6 at the 5% significance level. All the CD test values in Tables 1.5 and Tables 1.6 are above 1.6, indicating that the null hypothesis was not rejected at the 5% significance level. Therefore, the null hypothesis of parameters converging to the posterior distribution was satisfied.

As seen in the tables, the values of the inefficiency factor were all less than 100, which validated the use of the MCMC method (Nakajima and Watanabe 2012). This also confirmed that our posterior distribution sampled 10,000 times from the prior distribution is valid. Based on these results that both of our CNY and JPY samples converge to the posterior distribution, we used the MCMC method for both currencies.

In summary, the above results of the CD values and the inefficiency factor in Tables 5 and 6 indicate that the parameters of the TVP-VAR model in this study have changed during our test period.

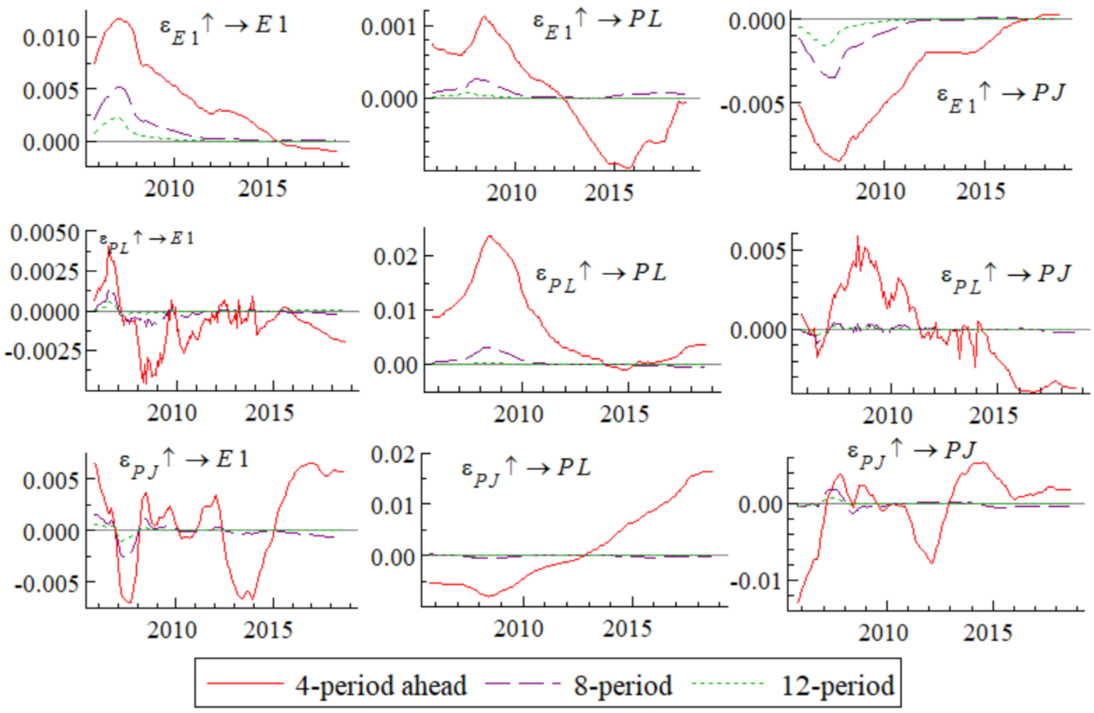
1.4.3 Results of the Impulse Response Analysis

In this section, the impulse response function of the TVP-VAR model is discussed. Since the parameter values of the TVP-VAR model change at each time point, the impulse response function can be drawn in a different diagram at each period. Figure 1.3 shows the shock and response of each variable of the time paths from the shock (4th, 8th, and 12th lag periods) at each period.

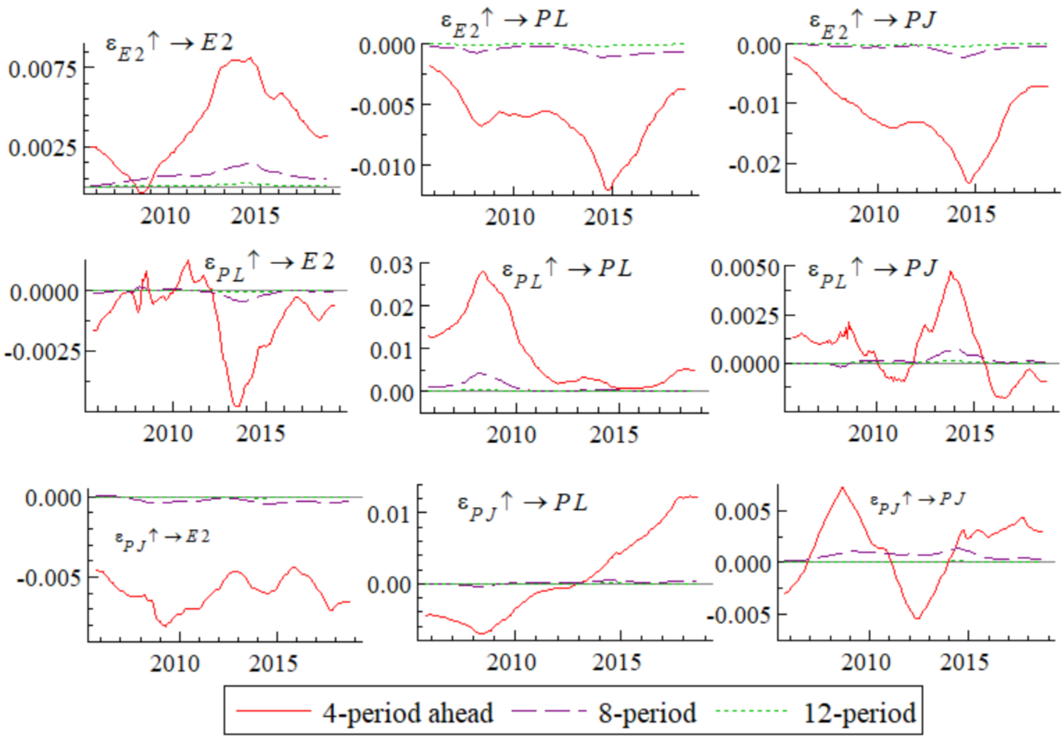
According to Figure 1.3(a), the impulse response value of the Chinese LNG import price from the CNY (E1) (4th lag period: $\varepsilon_{E1} \uparrow\rightarrow PL$) decreased positively from August 2005 to February 2007, but increased in March 2007. As the value of CNY appreciated after the financial crisis, the effects from the CNY on the LNG import price tended to decline from April 2008 to February 2012. However, from March 2012 to September 2018, the value of the Chinese LNG import price from the CNY (4th lag period : $\varepsilon_{E1} \uparrow\rightarrow PL$) became negative and increased with a negative tendency, and started to decrease toward zero from July 2015. It is discernible from Figure 1.3(a) that the CNY negatively affects the JCC crude oil price and the JCC price positively influences the LNG import price, meaning the CNY has negative impacts on the LNG import price.

According to Figure 1.3(b), the impulse response of the Chinese LNG import price against the JPY (E2) for the fourth lag period (4th lag period :$\varepsilon_{E2} \uparrow\rightarrow PL$) is similar to that of the JCC price against the JPY (E2) (4th lag period :$\varepsilon_{E2} \uparrow\rightarrow PJ$). Both the LNG import price and the JCC crude oil price were negatively correlated with the JPY, suggesting that JPY appreciation may lead to a drop in the Chinese LNG import and JCC crude oil prices. The 4th lag period for the $\varepsilon_{E2} \uparrow\rightarrow PL$ and $\varepsilon_{E2} \uparrow\rightarrow PJ$ between August 2005 to August 2014 has a declining trend, but after September 2014, the impulses from both of the currencies have been increasing toward zero.

Comparing the results of the CNY and JPY in Figure 1.3, the CNY has a lower impulse response than the JPY on both the LNG import and JCC crude oil prices at the 4th lag period. It is apparent that in both currencies, the impulse response effects at the 4th lag periods are higher than the other lag periods.

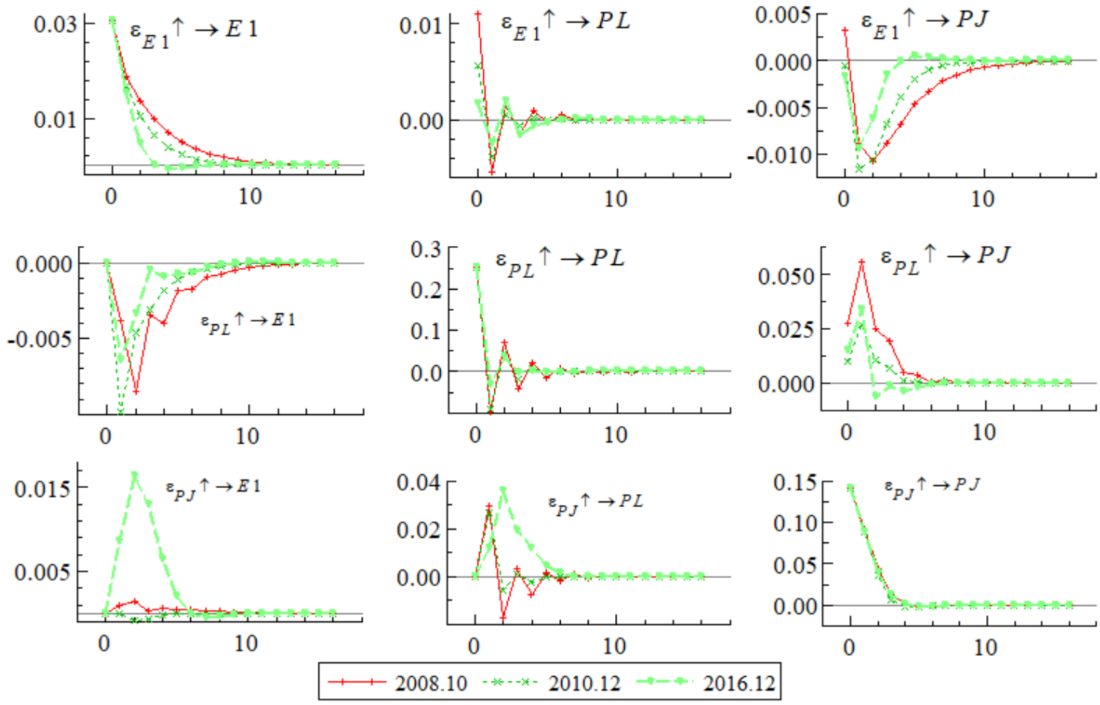


(a) CNY

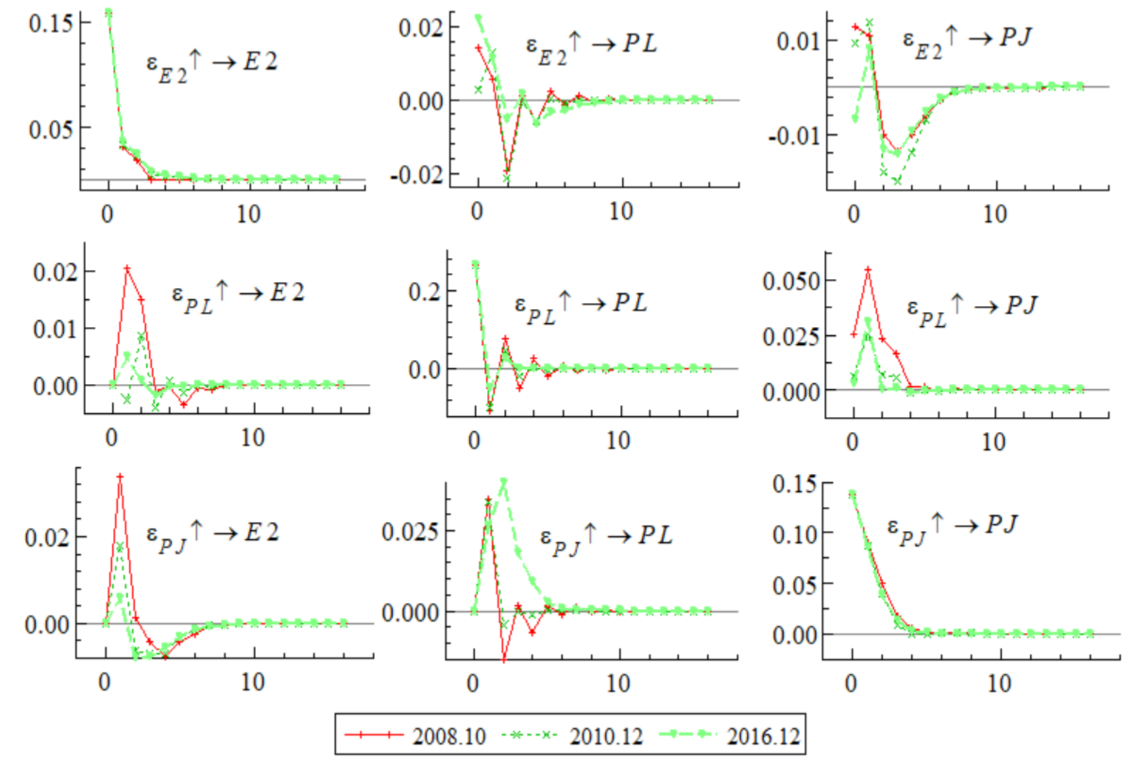


(**b**) JPY

Figure 1.3 Posterior mean of the impulse response functions.



(a) CNY



(**b**) JPY

Figure 1.4. Posterior mean of impulse response functions.

Figure 1.4 shows the impulse responses of October 2008, December 2010, and December 2016, which are likely to reflect the effects of the CNY monetary reform. According to Figure 1.4(a), the impulse response of the CNY on the Chinese LNG import price ($\varepsilon_{E1} \uparrow\rightarrow PL$) from October 2008 has a higher degree of response than those from December 2010 and December 2016. The reason for this increased impulse from the CNY on the LNG import price might be related to the monetary reform and the shock of the 2008 financial crisis. From Figure 4b, the impulse response of the JPY on the Chinese LNG import price ($\varepsilon_{E2} \uparrow\rightarrow PL$) from 2008 seems lower than those from December 2010 and December 2016. This might be because the JPY had more influence on the LNG import price than the CNY when the 2008 financial crisis occurred. It could be that the JPY was more susceptible to the oil price plummeted after the crisis.

Observing Figure 1.4 from a comparative viewpoint, the impulse response of JPY to JPY ($\varepsilon_{E2} \uparrow\rightarrow E2$) from October 2008 shows that the impulse stayed relatively stable for December 2010 and December 2016. On the other hand, the impulse response of CNY to CNY ($\varepsilon_{E1} \uparrow\rightarrow E1$) shows that the shock from October 2008 was larger than the shocks from the other two periods. Its lag effect remained up to the 10th examined period. This longer lag effect in the CNY compared to JPY is again likely to be the influence of governmental control regarding the CNY.

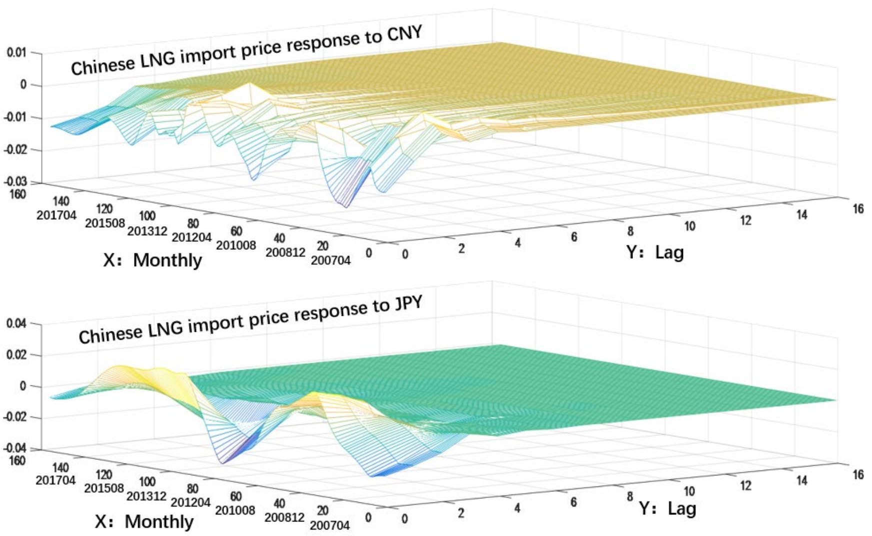


Figure 1.5. 3D impulse response functions. This is a 3D diagram created using MATLAB R2016a software. The upper part represents the impulse response function ($E1 \rightarrow PL$) of the Chinese LNG import price for the CNY E1, and the lower part represents the impulse response function ($E2 \rightarrow PL$) of the Chinese LNG import price for the JPY E2. The X-axis (year) represents each time point at the data period, the Y-axis (section) represents the time elapsed from the shock (0–16), and the Z-axis represents the response size (post-shock mean).

Figure 1.5 shows the three-dimensional (3D) plot that captures the overall image of the impulse response of the CNY and JPY on the Chinese LNG import price. From the figure, it is observable that the shock from the CNY to the LNG price (upper figure) is stable up until the 6th lag period while the shock from the JPY seems stable only until the 4th lag period. Presumably, the reason for JPY having a shorter period to absorb the shock is that the JPY is more capable to adjust to the free inflow and outflow of foreign capital while the CNY has been controlled under the regulations imposed by the Chinese government.

1.4.4. Pass-Through Rate Results

In Figure 1.6, the pass-through rate was calculated using the cumulative response value of the impulse in the first period from the shock of the CNY and JPY on the Chinese LNG import price.

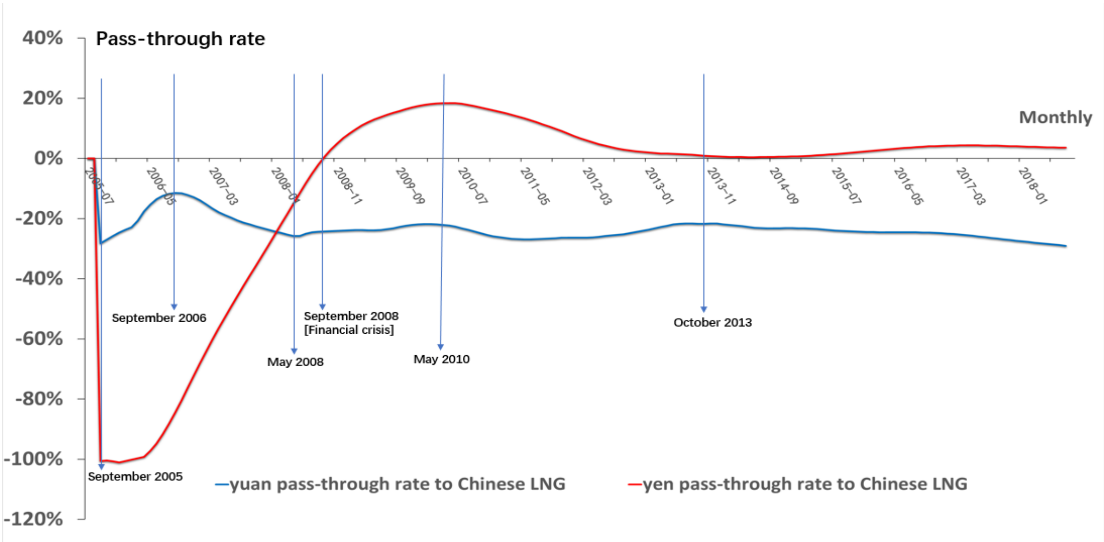


Figure 1.6. Changes in the pass-through rate for the CNY $(\mathrm{E1}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$ and JPY $(\mathrm{E2}_t, \mathrm{PL}_t, \mathrm{PJ}_t)$.

Let $R^{E1\to PL}_{pass-through}$ be the pass-through rate of CNY to the Chinese import LNG import price and $R^{E2\to PL}_{pass-through}$ be the pass-through rate of JPY on the Chinese LNG import price. Then, the figure indicates that from $R^{E2\to PL}_{pass-through}$, the pass-through rate of the JPY exceeded -100% in September 2005. On the other hand, the results of the $R^{E1\to PL}_{pass-through}$ show that the pass-through rate of the CNY in this period was only -25%. The figure illustrates that compared to CNY, the effects of the JPY began to decline after September 2005. $R^{E2\to PL}_{pass-through}$ decreased to 0% by September 2008, while $R^{E1\to PL}_{pass-through}$ did not decline by that much and fluctuated at around negative 25% from October 2006 to May 2008.

Then, from September 2008 to May 2010, $R_{pass-through}^{E2\to PL}$ increased toward a positive direction and reached a maximum of about 20%, while $R_{pass-through}^{E1\to PL}$ decreased slightly, but then seemed to be stable at around 20%. Besides, $R_{pass-through}^{E2\to PL}$ decreased to approach 0% from May 2010 to October 2013, while $R_{pass-through}^{E1\to PL}$ was stable near the 25% level from October 2008 to 2013. However, $R_{pass-through}^{E1\to PL}$ increased in the negative direction since October 2013, while $R_{pass-through}^{E2\to PL}$ declined to near zero.

These weakening impacts of JPY on the LNG import price were likely related to the CNY monetary reform. The year 2005 was the year when the Chinese government conducted the monetary reform, so the declining impact of the JPY after 2005 might be indicating that the CNY began to have more influence on the Chinese LNG import market after the monetary reform occurred. It is known that even if the CNY is managed by the government, this reform can be a significant influential factor in import price fluctuations (John et al. 1992). Hence, we conceived that it is reasonable to interpret the fact that the CNY began to play an important role in the Chinese LNG market after 2005 is related to the CNY monetary reform. It is probable that due to the effect of this 2005 CNY reform, the CNY pass-through rate on the LNG import price began to become higher than that of the JPY after 2008 and this higher CNY pass-through rate remained during our investigation period.

1.5 Discussions

First, the above results of Tables 1.5 and 1.6, and Figure 1.2 indicate that the parameters of the TVP-VAR model in this study have changed during our test period. This implies that importing companies and suppliers in the international LNG market need to consider the effects of the CNY fluctuations when purchasing LNG. Thus, the study results provide valuable price discovery information for Chinese LNG market stakeholders. Numerous studies indicate that the TVP-VAR model can be applied to analyze macroeconomic data and has its strength in estimating parameters of models that change with time (Primiceri 2005; Nakajima and Watanabe 2012; Shioji and Uchino 2009; Shioji 2010). However, this method has not been applied to understand the relationship between the Chinese LNG import market and the Chinese exchange rate market after monetary reform took place in China. Hence, the current study provides some evidence on how effective the TVP-VAR model can be when analyzing the energy price and currency rate relationship.

Second, Figure 1.5 revealed that the shock from the CNY to the LNG price (upper figure) was stable up until the 6th lag period, while the shock from the JPY was stable only until the 4th lag period. These results are consistent with the conclusion of Shinkai (2011), Choudhria and Hakura (2015), and Pennings (2017) suggesting that the exchange rate pass-through to import prices is incomplete for a large number of countries. The result of the impulse response analysis indicated that as the volatility of the CNY increased, the exchange rate risk in the LNG trading market gradually transferred from the JPY to the CNY after 2005. The results in Figure 1.6 also indicate that compared to JPY, the influence of the CNY began to intensify after 2005. These results imply that since the July 2005 currency reform, the impact of the CNY on the LNG import market became stronger. This suggests the importance of considering the effects of monetary reform for understanding the Chinese LNG import and the exchange rate relationship.

1.6 Conclusions

This paper provided an overview of the empirical methodology of the TVP-VAR model with stochastic volatility, as well as its application to the pass-through rate of the JPY and CNY on the Chinese LNG import price. The empirical application of the TVP regression model revealed the importance of incorporating stochastic volatility into parameter estimation when analyzing the impact of the exchange rate on the LNG import price.

The results of our study indicate that if a new CNY monetary reform takes place in the future, the effects of JPY on the Chinese LNG price will be reduced and those of the CNY on the Chinese LNG price is likely to become stronger. The study suggests the importance of considering the CNY fluctuation range when discovering or forecasting the price of the Chinese LNG import price. These findings imply that the LNG import price will be more stabilized when the CNY is controlled by the Chinese government.

Hence, the study indicates the significance of considering effects of the exchange rate on an energy market when it is likely to be influenced by a monetary reform of the importing country. The study also suggests the importance of applying the TVP-VAR model instead of using the conventional VAR model when the parameters in the VAR model are time-variant.

Finally, our study is limited in a way that it did not consider other factors such as the freight and insurance premiums that could influence the pass-through rate on the LNG import price. Hence, for our future study, we are hoping to investigate the pass-through rate when these factors are considered in the TVP-VAR model

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Part 2: The linkages among Chinese coal and international fossil fuel markets

2.1 Introduction

As coal is an important input factor for production in China, the country faces significant economic uncertainty resulting from coal price fluctuations (Guo et al., 2016). A decrease in domestic coal price could reduce the cost for industrial consumers, and thus energy price changes could be regarded as supply shocks to the Chinese economy (Li et al., 2019).

As the world's largest producer and consumer of coal, China needs to understand the relationship between Chinese domestic coal and international energy prices, important for formulating policies to stabilize the domestic coal price. If the domestic coal market is related to the international coal, crude oil, and natural gas markets, it implies that companies involved in assuring fuel sources for the coal-using segments must consider the effects of international coal, crude oil, and gas markets when they decide their coal consumption levels (Honorata *et al.,* 2020). It also indicates that policymakers seeking to stabilize the coal price must consider the sharp increase or decrease in the global energy price to mitigate the effects of the domestic coal price change on economic growth (Li *et al*., 2020).

Numerous papers have investigated the long-run price relationship between crude oil and imported natural gas in the international market (Ji *et al*., 2014; Li *et al*., 2017). For example, Ji *et al*. (2014) revealed a long-run correlation between crude oil prices and the regional natural gas import price among the North American, European, and Asian markets. Li *et al*. (2017) investigated the price relationship between the natural gas and the coal markets to find that they have cointegration relationships. Li *et al*. (2017) also indicated that the relationship between Chinese domestic coal prices and international natural gas became apparent after the market reforms in the Chinese coal market.

The above research did not test the dynamic relationship among the fossil fuel markets. However, Ates and Huang (2011) applied the recursive cointegration method to show that the price relationship between crude oil and natural gas markets had changed dramatically from April 4, 1990, to June 23, 2009. This study is among the few studies investigating the dynamic relationship among the fossil fuel markets. However, little has been done to identify the dynamic relationship for the Chinese fossil fuel markets.

The dynamic relationship between Chinese coal and international coal and crude oil prices is only analyzed based on the dynamic conditional correlation (DCC) model by Li *et al*. (2019). The DCC shows how price volatility in one energy market relates to price volatility in another energy market. However, the DCC does not identify the cointegration relationships among the market prices. The current study's first point of divergence from Li *et al*. (2019) is that it uses the national overall coal price index, whereas Li *et al*. (2019) used the Chinese Qinhuangdao (QHD) coal price, which only considers the coal price of a particular area. Second, our study is different from other relevant studies because we apply the recursive cointegration test to capture the dynamic relationship between Chinese coal and international natural gas markets.

Li *et al*. (2019) found that the co-movement between Chinese coal and international coal and crude oil prices have different trends before and after mid-2008. This result indicates that it might be necessary to isolate some unique economic events as endogenous structural breaks and consider the time series data (Byrne and Perman, 2006). For example, many studies have suggested that the 2008 financial crisis caused immense impacts on energy markets (Aruga and Kannan, 2020; Yuan, Liu, and Wu., 2010). Additionally, Ling *et al*. (2013) suggest the importance of incorporating structural breaks when analyzing macroeconomic time-series data.

Due to structural breaks, understanding the dynamic relationship between international energy prices and Chinese coal prices is important for stakeholders and policymakers. This study shows that if the dynamic relationship between coal and international fossil fuel markets changes within the investigated period, it can imply that stakeholders and policymakers need to consider changes in the relationship between domestic coal prices and international energy prices to understand coal price movements and to conduct more accurate forecasting. We expect that the results of this study can provide valuable price discovery information for Chinese coal market stakeholders and policymakers.

We expect that the Chinese domestic coal market will not have a relationship with the international coal, crude oil, and natural gas market before 2008. The Chinese domestic coal market will begin to have a relationship with them after 2008. This is because China had enough supply from its domestic production and even exported its coal until mid-2008, suggesting that it was independent of the international energy market (Li *et al*., 2020). However, after the 2008 financial crisis, China started to import a fair amount of coal from the international coal market. One probable reason for this is that the 2008 financial crisis led to a decline in international energy prices (Joo *et al*., 2020), and the cost of importing coal was reduced. Furthermore, due to the implementation of a 4 trillion yuan ($586 billion) stimulus plan, the Chinese economy was still at a high growth stage relative to foreign economies since 2008, which led China to increase its coal demand (Yuan, Liu, and Xie., 2010).

We also anticipate that the drastic changes in domestic and international gas markets in the 2010s might have influenced the relationship between the Chinese coal and international fossil fuel markets. First, as the shale gas revolution causes downward pressure on international gas markets (Aruga, 2016), the Chinese coal market was affected by this revolution in the 2010s. Second, as the Chinese government announced an increase in natural gas consumption between 2016 and 2020 (NEB[1)], 2016) to improve its air quality by reducing PM2.5 and CO2 emissions, China may shift from coal to natural gas consumption. Chinese natural gas consumption increased by 18% from 2018, accounting for 22% of global gas consumption net growth (BP[2)], 2019). Thus, the relationship between the Chinese coal and international fossil fuel markets might have changed in the 2010s.

We explain the research methodology in the next section. The second section describes the dataset employed in this study. Finally, the results and conclusions are introduced.

2.2 Methods

The traditional Johansen cointegration test can only detect the price linkage during the whole period and cannot evaluate whether the price linkage changes with time. However, the recursive Johansen test reveals how the cointegration relationship changes during the investigated period (Aruga, 2020). The recursive cointegration test can reveal the dynamic time-path of international energy prices on domestic coal prices. By applying the recursive cointegration test, this study provides dynamic information on the impact of international prices on domestic coal prices to stakeholders of the Chinese coal market. To confirm the validity of the recursive cointegration test, we apply the conventional Johansen test for periods identified to have cointegration relationships. Thus, this study applies two cointegration tests: the recursive and conventional Johansen tests (Johansen & Juselius, 1990).

Before performing a cointegration test on the price series, integrating the test variables is examined through stationarity tests. Therefore, the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS unit root tests are performed on our time series data. We then identified the optimal lag orders of the vector autoregressive (VAR) model based on the Schwarz information criterion (SIC).

Let P_t be the column vector of the k price series in this study. Then, the mathematical representation of VAR is given by:

$$\Delta P_t = A_0 + A_1 \Delta P_{t-1} + \cdots + A_n \Delta P_{t-n} + \varepsilon_t \tag{1}$$

where Δ is the first difference operator, A_0 is a constant vector ($k \times 1$), $A_1 \cdots A_n$ are matrices of coefficients to be estimated ($k \times k$), n is the lag order, and ε_t is the $k \times 1$ vector of error terms.

Then the Johansen test is performed using the following vector error correction model:

$$\Delta P_t = \prod P_{t-1} + \sum_{i=1}^{n-1} \Gamma_i \, \Delta P_{t-i} + \gamma_t, \qquad t = 1, \cdots, T \tag{2}$$

where Δ is the first difference operator, $\prod = \sum_{i=1}^{n} A_i - I$, and $\Gamma_i = -\sum_{j=i+1}^{n} A_j$. The number of cointegration vectors is determined by the rank of the Π matrix in Eq. (2). If rank (Π)=0, the matrix is null, and the price variables will not be cointegrated. If Π is of rank k, the price series is stationary. If $1 < rank(\Pi) < k$, there are cointegration relations among the price variables. γ_t is a vector of independent and identically and normally distributed random disturbance terms.

The model in equation (2) is also applied to the recursive Johansen test. Following Aruga and Kannan (2020) and Tang and Aruga (2021), first, the estimation algorithm automatically treats the first k observations as the initial base sample. Second, additional observations are added with shifts from the base sample. Then, the trace statistics are estimated recursively for each iteration. Finally, this recursive estimation continues until the final sample period, June 2020, is reached. The estimation is conducted by CATS 2.0 of RATS Version 10.0. The results are presented in graphs and are evaluated graphically (Tang and Aruga, 2021).

2.3 Data

The study uses monthly data covering the period 2000:01–2020:06. As different provinces in China use different coal prices, the Chinese price indices of domestic coal industrial sectors are used. These data were obtained from the CEINET[3)] Statistics Database. The international coal, oil, and natural gas prices are acquired from the World Bank commodity markets[4)].

The Japanese liquefied natural gas (LNG) and the Australian port thermal coal are used in the study. These data are obtained from the World Bank. Although the Japanese LNG price is based on a long-term contract it is often used as an indicator for the Asian LNG market (Martono and Aruga, 2018), and hence, it is meaningful to investigate the relationship with the Chinese coal market. All price data are shown in Figure 2.1.

As energy prices have different units, they are standardized by the following formula:

$$Z = \frac{P - \mu}{\sigma}, \tag{3}$$

where Z is the normalized value of P; P denotes the price variable in this study, and μ, and σ are the mean and standard deviation of P.

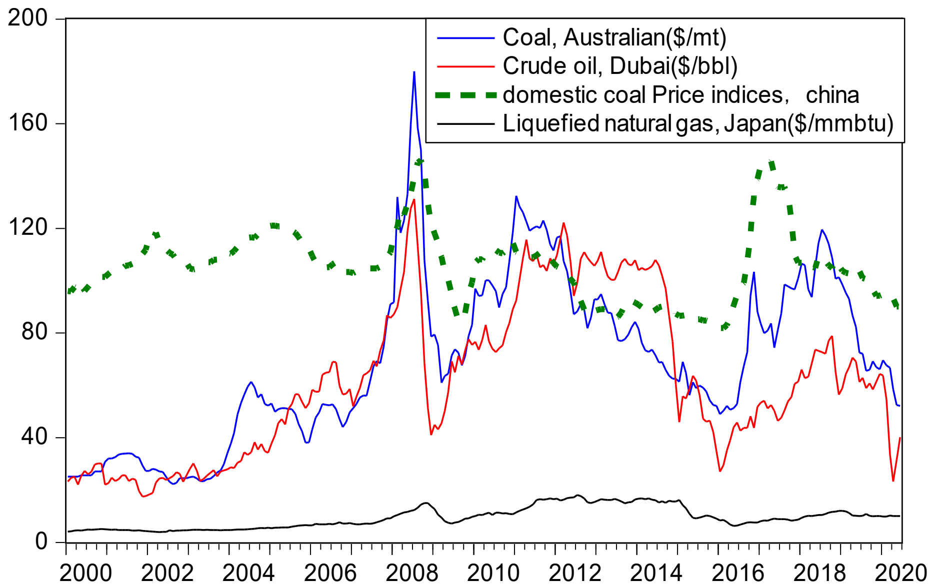

Figure 2.1 Plots of the price data

2.4 Results

2.4.1 Unit root test

Table 2.1 shows the unit root test results for the level and the first differences with constant and trend. The result shows that all price series are non-stationary at their level data but are stationary when first differencing them at the 1% significance level. Thus, all price series are first-order integrals in the entire test period.

Table 2.1 Unit root tests.

Variables	Level Data (t-Value)			First Difference Data		
	ADF	PP	KPSS	ADF	PP	KPSS
Australian coal	-2.39	-2.33	0.95*	-11.71*	-11.78*	0.1
Dubai crude oil	-2.51	-2.04	0.78*	-9.53*	-8.75*	0.16
Japanese LNG	-2.05	-1.73	1.00*	-6.83*	-9.50*	0.12
Chinese coal	-3.69	-3.02	0.22*	-5.43*	-6.91*	0.05

Note) * Significant at the 1% significance level

2.4.2 Cointegration tests

Table 2.2 illustrates the results of the Johansen test. The table indicates that the Australian coal and Dubai crude oil prices are not cointegrated with the Chinese domestic coal price for the entire period (2001:01–2020:06). This might be because the Chinese government has been controlling the domestic coal price until 2013 (Zhang *et al.*, 2018). On the contrary, the table suggests the Chinese domestic coal and the Japanese natural gas markets have a cointegration relationship for the entire period. This cointegration is likely due to natural gas being a direct substitute for coal. To reduce its carbon emissions, China began to import natural gas to replace coal (Ding *et al.*, 2017), decreasing its coal-oriented energy source from 64% to 58% while increasing the natural gas ratio to 10% during 2015–2020 (National Energy Board, 2016). This shift in energy sources from coal to natural gas may have affected the price linkage between Chinese coal and the Japanese natural gas market.

Table 2.2 Cointegration tests

Variables	H0: rank = r	Trace test	Max test
Entire period (2001:01–2020:06)			
China coal vs Australian coal	r = 0	24.16**(0.002)	19.69**(0.006)
	r ≤ 1	4.47**(0.003)	4.47**(0.003)
China coal vs Dubai crude oil	r = 0	25.81**(0.001)	21.51**(0.003)
	r ≤ 1	4.31**(0.037)	4.31**(0.037)
China coal vs Japanese LNG	r = 0	26.36**(0.000)	23.27**(0.000)
	r ≤ 1	3.08(0.108)	3.08(0.108)

Note) ** Significant at the 5% significance level. The value inside the parentheses is a p-value.

2.4.3 Recursive Johansen test

Figure 2.2 shows the results of the recursive Johansen test. The figure presents the dynamic changes in the cointegration relationships. The value in the vertical axis denotes the ratio of the critical value and trace statistics. When this value is larger than one, it indicates that the two series are cointegrated. Thus, the test results show that the price relation of the whole interval is dynamic cointegration. Fig (a) indicates that the Chinese domestic coal price is only cointegrated with the Australian coal price between January 2008 and July 2013. Fig (b) indicates that the Chinese domestic coal price is cointegrated with the Dubai crude oil price from February 2009 to November 2014. Fig (c) reveals that the Chinese domestic coal price is cointegrated with the Japanese natural gas from June 2008 to November 2008 and from December 2017 to June 2020.

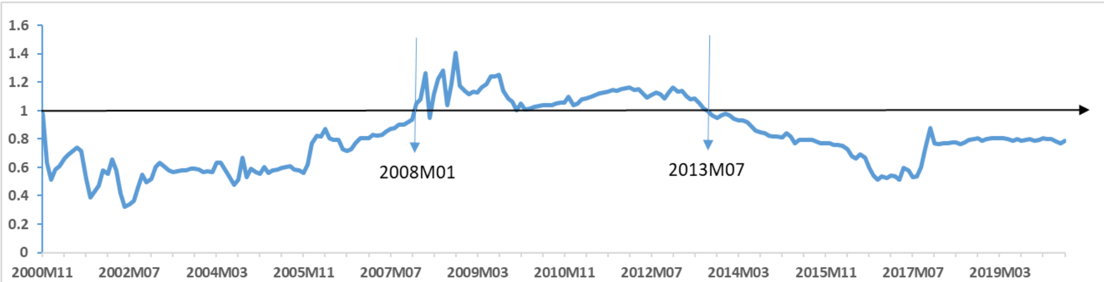

Fig. (a): China coal vs Australian coal

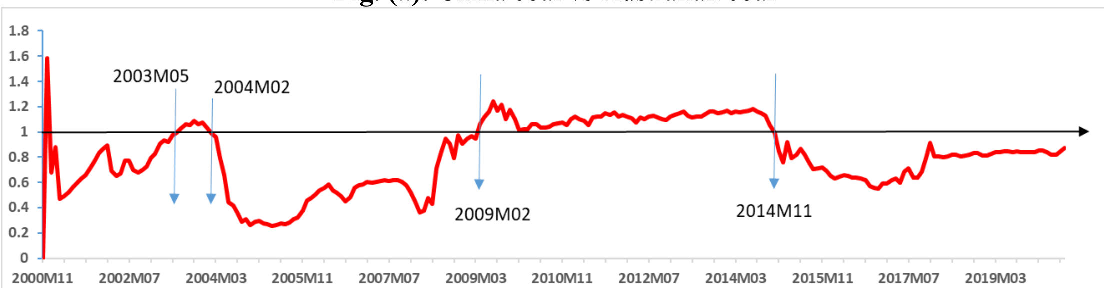

Fig. (b): China coal vs Dubai crude oil

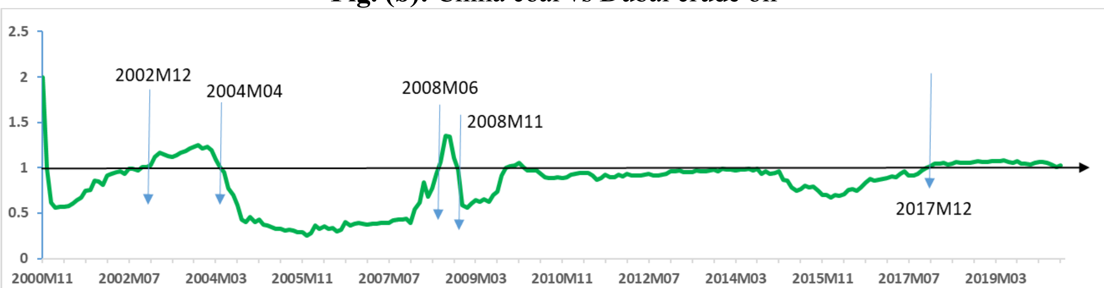

Fig. (c): China coal vs Japanese natural gas

Figure 2.2: the recursive Johansen test between Chinese domestic coal price and prices of Australian coal, Dubai crude oil, and Japanese natural gas

The Johansen test is conducted on periods determined to have such relationships to verify the cointegration relationships identified by the recursive cointegration test. The unit root tests were conducted, results are as shown in Table 2.1. The results suggested that all price series are non-stationary at their level data and become stationary for the first differenced series at the 5%

significance level. As seen in Table 2.3, the Johansen test reveals that the test variables are cointegrated during the specific periods identified by the recursive cointegration test. The Chinese domestic coal price was cointegrated with the Australian coal price from January 2008 to July 2013. The Chinese domestic coal price was cointegrated with the Dubai crude oil price from February 2009 to November 2014. The Chinese domestic coal price is cointegrated with the Japanese natural gas price from December 2017 to June 2020.

Table 2.3. Cointegration tests

Variables	H0: rank = r	Trace test	Max test
period (2008:01–2013:07)			
China coal vs Australian coal	r = 0	29.04**(0.019)	22.40**(0.017)
	r ≤ 1	6.64(0.38)	6.64(0.38)
period (2009:02–2014:11)			
China coal vs Dubai crude oil	r = 0	32.06**(0.007)	22.89**(0.014)
	r ≤ 1	9.18(0.16)	9.18(0.16)
period (2017:12–2020:06)			
China coal vs Japanese LNG	r = 0	28.23**(0.024)	21.02**(0.028)
	r ≤ 1	7.21(0.322)	7.21(0.322)

Note) ** Significant at the 5% significance level. The value inside the parentheses is a p-value.

2.5 Discussion

The results indicate that the Chinese domestic coal market is not related to the international coal, crude oil, and natural gas market before 2008. However, the Chinese domestic coal market's relationship with them became apparent after 2008. One probable reason for this is that the 2008 financial crisis has influenced the relationship between the Chinese coal and international fossil fuel markets (Tang and Aruga, 2021). The results also show that the relationships between the Chinese coal and international fossil fuel markets had changed during the 2010s. It became apparent that the Chinese domestic coal market was cointegrated with the international natural gas market after 2018. This could be because the shale gas revolution in the 2010s had influenced Chinese coal and international fossil fuel market relationships.

2.6 Conclusions

The above results have the following implications. First, the long-run relationship between the Chinese coal and international fossil fuel markets were changing during the study period, implying that importing companies in China must consider the impact of the dynamic relationship between international energy prices and domestic coal prices to identify coal price movements when purchasing coal. Second, we found that the Chinese domestic coal and international natural gas markets became cointegrated after 2018, signifying that after 2018, policymakers must consider the impact of international natural gas prices when formulating a policy to stabilize the Chinese coal price. Thus, this study provides valuable price discovery information for Chinese coal market stakeholders and policymakers.

As natural gas is one of the major energy sources after the 13th Five Year Plan of China5), stakeholders and policymakers of the Chinese coal market must consider international natural gas prices for identifying Chinese coal price movements and generate more accurate expectations.

These results of this study will provide important information for the Chinese government to substitute coal with natural gas to address the climate change issue until it can totally replace its fossil fuels with renewable sources.

This empirical investigation is limited to investing the Chinese coal market only from a price perspective. Further studies must incorporate other relevant variables that are important for understanding the demand and supply structure.

NOTES

1) National Energy Board(NEB). (01/17/2017 updated) The 13thFive-Year Plan for Energy Development(Written in Chinese).page.<http://www.nea.gov.cn/2017-01/17/c_135989417.htm>,10/25/2020 referred.13

2) British Petroleum (BP)(07/28/2019 updated) Annual report page.<https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2019-full-report.pdf.> 8/10//2020 referred.

3) CEINET Statistics Database(07/28/2020 updated) month page.< https://db.cei.cn/> 8/10//2020 referred.

4) Commodity markets of the world bank. (07/28/2020 updated) month data page. < https://www.worldbank.org/en/research/commodity-markets> 8/10//2020 referred.

5) National Energy Board. (01/17/2017 updated) The 13th Five Year Plan for Energy Development(Written in Chinese) page.
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Part 3: Effects of the 2008 Financial Crisis and COVID-19 Pandemic on the Dynamic Relationship between the Chinese and International Fossil Fuel Markets

3.1 Introduction

According to the WHO report (WHO 2020), Coronavirus disease 2019 (COVID-19) was first reported in Wuhan City, Hubei Province of China, in late December 2019. In response to minimize the threat of the coronavirus, the Chinese government sealed off Wuhan City on January 23, 2020, and then all the cities in China were compelled to restrict business activities (Wu et al. 2020). Subsequently, Covid-19 was confirmed as a widespread pandemic over the world, affecting many industrial sectors, and restrictive measures are used to prevent the spread of the virus (Aruga et al. 2020).

With these restrictions, many industries, including agriculture, manufacturing, finance, education, healthcare, sports, tourism, and food are largely at a halt, causing adverse impacts on energy demand and consumption (Jiang et al. 2021). According to the International Energy Agency (IEA) (2020), it is predicted that countries in full lockdown will experience a 25% decline on average in energy demand per week, where countries in partial lockdown will decline 18% on average. The Asian demand for oil and gas was expected to fall by 15 percent, with the possibility of a 17 percent drop due to the pandemic in 2020 (Energy 2020). According to the Chinese government (SIPA 2020), national energy consumption and power demand declined 2.8% and 6.5%, respectively, in the first quarter of 2020 compared to that of 2019.

The COVID-19 shock on energy markets in the Asian-Pacific region became more evident in the fossil fuel market. The World Bank calculated that there was a 63.5% drop in Dubai crude oil price, a 15.9% drop in the Australian coal price, and a 1.2% increase in the Japanese Liquefied Natural Gas price from January 2020 to April 2020. In China, the domestic petroleum and natural gas price indices fell 31.4% and 58.6%, respectively, during the same period (CEINET Statistics Database 2021). We expect that the drop in fossil fuel prices in 2020 is related to the decline in oil consumption due to the COVID-19 outbreak and political factors affecting the supply side like the price war between Saudi Arabia and Russia in March 2020 (Turak 2020). However, in this study, based on Fama's efficient market hypothesis (Fama 1991), we focus on the price itself rather than the factors behind the price changes assuming that the demand and supply factors are incorporated in the market price.

China is an interesting case study for the following three reasons (Norouzi et al. 2020). First, China is the first country suffering from the COVID-19, which is feasible for capturing the early stage of the shocks of the COVID-19 crisis. Second, it is the second-largest economy and largest developing country, having the highest fossil fuel consumption in the world. Thus, we believe conducting a case study on China can serve as a proxy for understanding the impacts of the COVID-19 crisis on fossil fuel-consuming countries. Finally, China is the world's largest energy importer, and thus, we can learn from this case study how an energy importing country is affected by the COVID-19 pandemic.

Furthermore, the above drastic price fluctuations in the Chinese and international fossil fuel prices will increase the risk of uncertainty for energy trading participants and policymakers. To better understand the above drastic price fluctuations caused by the COVID-19 crisis, it would be interesting to compare the impacts with another well-known exogenous shock affecting the fossil fuel market: The 2008 financial crisis. Before the 2008 financial crisis, energy-producing companies increased their investments significantly. However, when global energy demand dropped sharply due to the crisis, companies addressed the drastic decline in cash flow with a reduction of prices (Hauser et al. 2020). Spatt (2020) suggests that the examples of two crises analyzed simultaneously can lead to more insight than a single one to help understand the covid-19 crises and the causes and consequences of both crises. The 2008 financial crisis reflects the infection of the financial system due to excess leverage and poor-quality mortgage loans while the COVID-19 crisis is related to a substantial global economic shock due to the outbreak of the coronavirus.

We expect that the dynamic relationships between the Chinese and international fossil fuel markets are changing differently from the 2008 financial crisis during the COVID-19 pandemic periods. The impact of the 2008 financial crisis on the energy market is related to financial market behavior, which will act differently in bear and bull markets (Mollick and Assefa 2013). So, the relationship between the variables may be subject to drastic changes during the crisis (Mollick and Assefa 2013), and thus, we expect that it would be more difficult for the stakeholders of the fossil fuel market to predict the effects of the impact from the 2008 financial crisis.

On the other hand, the information for the impact of the COVID-19 crisis on the energy market could be predicted according to historical production data announced by the government. When a lockdown is announced by the government it is easy to forecast that the energy demand will decrease. Thus, energy stakeholders can expect beforehand that the COVID-19 crisis would cause a sharp drop in energy prices when a lockdown is conducted. If the cause and timing of the event are known to the market participants, effects of the shock will likely be quickly incorporated into the market, and hence, we anticipate that the shock from the COVID-19 crisis will have little change on the linkages between the Chinese and international fossil fuel markets.

Therefore, analyzing the impacts of the 2008 financial crisis and the COVID-19 pandemic on the relationship between the Chinese and international fossil fuel markets will provide useful information for the market participants and policymakers of the fossil fuel markets to hedge against the uncertainty and risk involved with the energy price fluctuations related to the economic crises. If the study identifies that the dynamic relationships between the Chinese and international fossil fuel markets are changing during the crisis periods, it will imply that stakeholders and policymakers trading between the Chinese and international fossil fuel markets need to consider the shocks from these crises in their price discovery processes. Thus, we expect that the study will provide valuable information for stakeholders and policymakers managing risks in the Chinese energy markets.

We describe and explain the previous research in the second section. The third section presents the materials and methodology of the study. Then in the fourth section, we will report the results of the analyses performed in the study. Finally, the discussion and conclusion will be introduced in the fifth and last sections.

3.2 Previous Research

Numerous papers have investigated the impact of the COVID-19 epidemic crisis on different countries and regional energy markets (Aruga et al. 2020; Nyga-Lukaszewska and Aruga 2020; Bahmanyar et al. 2020; Norouzi et al. 2020; Jiang et al. 2021). Aruga et al. (2020) found that a long-run relationship holds between the COVID-19 cases and energy consumption and that the COVID-19 cases have a positive effect on Indian energy consumption. Bahmanyar et al. (2020) suggested that the energy consumption profiles reflect the difference in peoples' activities in different European countries using various measures in response to the Covid-19 pandemic. Norouzi et al. (2020) suggested that the elasticity of petroleum and electricity demand toward the population of the infected people in China is −0.1% and −0.65%, respectively. Jiang et al. (2021) showed that although the overall energy demand declines, the extra energy for COVID-19 fighting is non-negligible for stabilizing energy demand, and the energy recovery in different regions presents significant differences.

Next, some studies brought important implications in the risk management of energy during the pandemic (Akhtaruzzaman et al. 2020; Chang et al. 2020). Akhtaruzzaman et al. (2020) showed that oil supply industries benefit from positive shocks to oil price risk in general, whereas oil and financial industries react negatively to positive oil price shocks. Chang et al. (2020) believed that there are strong cross-sector herding spillover effects from US fossil fuel energy to renewable energy, especially before the 2008 financial crisis, while the US fossil fuel energy market has a significant influence on the European and Asian renewable energy returns during the COVID-19 pandemic.

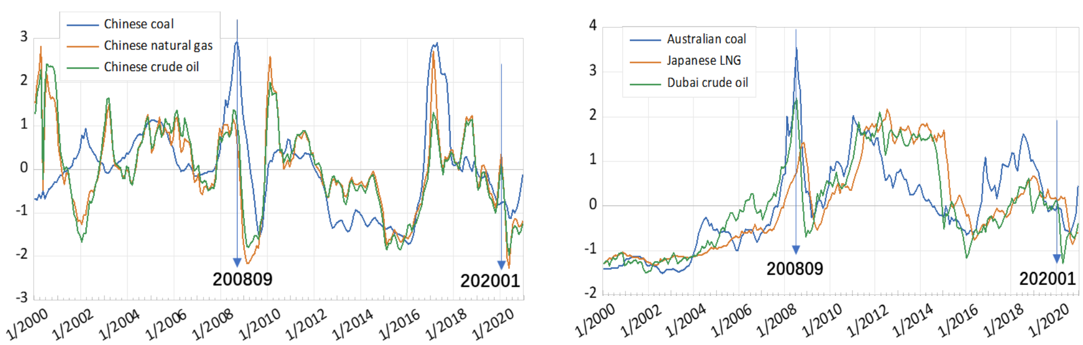
On the other hand, there is a large amount of literature studying the volatility spillovers in commodity and financial markets to understand the cross-market linkages during the

COVID-19 crisis (Bouri and Lei et al. 2021; Bouri and Lucey et al. 2021; Shahzad et al. 2021). For example, Bouri et al. (2021a) examine the realized volatility connectedness across 15 international commodity futures showing strong and moderate levels of volatility connectedness among energy and metals and moderate connectedness within the group of agricultural commodities. Shahzad et al. (2021) indicated that the impact of volatilities on the inter-sectoral stock market is asymmetric and time-varying during the COVID-19 period.

However, few prior studies examined whether the dynamic cointegration relationships between the Chinese and international fossil fuel markets are changing during periods related to the 2008 financial crisis and the COVID-19 pandemic. Unlike the previous study, the current study is among the first studies to explore this issue. In addition, recently, many studies investigating energy market linkages use the cointegration methods (Aruga and Kannan 2020; Hu et al. 2020) but up until now, no studies have applied both the recursive cointegration test and the VAR or VECM model including the crises as dummy variables for identifying market linkages. By including the dummy variable, the model can grasp the impact of the crisis on the dynamic relationships. The study not only contributes to understanding how the crises influenced the dynamic relationship between the Chinese and international energy sectors but also becomes a good reference for analyzing the effects of events causing economic shocks on other Asian-Pacific countries.

3.3 Materials and Methods

To identify the dynamic cointegration relationships between the Chinese and international fossil fuel markets during the 2008 financial crisis and COVID-19 pandemic, we used the recursive Johansen cointegration test developed by Hansen and Johansen (1993). Our cointegration tests are performed between January 2000 to December 2020.



(**a**): Chinese fossil fuel price (**b**): International fossil fuel price

Figure 3.1. Plots of the Chinese and international fossil fuel prices.

As Chinese and international fossil fuel prices have different units, they are standardized as shown in Figure 3.1. First, we used the monthly price indices of the domestic coal, natural gas, and petroleum industrial sectors to represent the Chinese fossil fuel market because different provinces of China use different fossil fuel prices. These price indices are obtained from the CEINET statistics database (2021). Second, for the international fossil fuel prices, we used the Australian coal, Dubai crude oil, and Japanese liquefied natural gas (LNG) prices. These international fossil fuel prices are gathered from the World Bank (2021).

It is necessary to test the stationarity of time series data and identify the optimal lag orders before performing a cointegration test. For this purpose, we conducted the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS unit root tests on our time series data. Trend and intercept are included in the unit root tests. The Akaike Information Criterion (AIC) is used for selecting the optimal lag length for the unit root tests, and the Parzen kernel is used for the estimations. Table 1 illustrates the results of these tests. The result shows that all our test variables are non-stationary at their level data but are stationary when first differencing them at the 5% significance level.

Table 3.1. Unit root tests.

Variables	Level Data (t-Value)			First Difference Data		
	ADF	PP	KPSS	ADF	PP	KPSS
Australian coal	−2.46	−2.41	0.85 *	−11.5 *	−11.59 *	0.05
Japanese LNG	−1.81	−1.73	0.92 *	−7.45 *	−9.44 *	0.19
Dubai Crude-oil	−2.55	−1.97	0.67 *	−9.67 *	−8.92 *	0.18
China coal	−2.60	−3.10	0.38 *	−4.55 *	−6.90 *	0.03
Chinese natural gas	−3.27	−4.12	0.37 *	−7.45 *	−13.4 *	0.02
Chinese crude oil	−2.88	−3.75	0.43 *	−12.89 *	−12.88 *	0.02

Note: * Significant at the 5% significance level.

Table 3.2. Optimal lag orders.

Relationship Between Variate	Lag	Lowest SC
Chinese coal vs Australian coal	2	−1.35 *
Chinese coal vs Dubai crude oil	2	−1.62 *
Chinese coal vs Japanese LNG	2	−2.38 *
Chinese crude oil vs Australian coal	2	−0.41 *
Chinese crude oil vs Dubai crude oil	2	−1.04 *
Chinese crude oil vs Japanese LNG	4	−1.60 *
Chinese natural gas vs Australian coal	2	−0.02 *
Chinese natural gas vs Dubai crude oil	2	−0.69 *
Chinese natural gas vs Japanese LNG	4	−1.28 *

Note: The * symbol represents the lowest value of SC.

As the precondition of the cointegration test was satisfied, we performed the recursive Johansen cointegration test between the Chinese and international fossil fuel prices. To apply the recursive cointegration test, we identified the optimal lag orders to be included in the test model based on the vector autoregressive (VAR) model. The optimal lag lengths are determined based on the Schwarz Information Criterion (SC). The lag orders selected by the criterion are based on the lowest SC value. The results of the optimal lag orders are presented in Table 3.2.

The algorithms for recursive estimation are first performed by estimating the Johansen trace test over an initial sample (Aruga and Kannan 2020). Thus, the base initial sample will be automatically treated as the first k observations by the program. Then, additional observations are added to this base sample, and at each iteration, the trace statistic is estimated recursively. Finally, this recursive estimation continues until the final sample period, December. 2020, is reached. The above Algorithms for the recursive estimation process are used in the CATS 2.0 package in RATS Version 10.0. The results are plotted and evaluated graphically. The recursive Johansen trace statistics are reported in the graph, and the critical values larger than one in the graph indicate that the two series are cointegrated.

To check the cointegration relationship for the whole period investigated in the study, we also performed the Johansen test (Johansen and Juselius 1990).

Finally, to find out if the changes in the cointegration relationship identified by the recursive cointegration test were related to the changes in the Chinese and international fossil fuel prices due to the shocks from the 2008 financial crisis and COVID-19 pandemic, we applied the VAR and VECM models by including these events as dummy variables.

To verify whether the VAR or VECM model should be used, we use the results obtained from the Johansen test. If the Johansen test revealed that there is not a cointegration relationship between the Chinese and international fossil fuel prices, the VAR model is used while the VECM model is applied when a cointegration relationship is found.

The mathematical representation of the VAR model is given by:

$$\Delta P_t = \beta_0 + \beta_1 \Delta P_{t-1} + \cdots + \beta_n \Delta P_{t-n} + \varepsilon_t \tag{1}$$

where P_t is the column vector of the k fossil fuel price series of this study. Δ is the first difference operator, β_0 is a constant vector $(k \times 1)$, $\beta_1 \cdots \beta_n$ are matrices of coefficients to be estimated $(k \times k)$, n is the optimal lag order, and ε_t is the $k \times 1$ vector of error terms.

The mathematical representation of the VECM model is given by:

$$\Delta P_t = \lambda E P_{t-1} + \sum_{i=1}^{n-1} \phi'_{t-i} \Delta P_{t-i} + \varepsilon_t \tag{2}$$

here the difference from equation (1) is that in this equation the error correction term EP_{t-1} is included in the VAR model. The error correction term captures the long-run relationship between the Chinese and international fossil fuel markets.

To capture the impacts of the 2008 financial crisis and COVID-19 pandemic on Chinese and international fossil fuel markets for analyzing the change in the relationship between the Chinese and international fossil fuel markets, we applied the VAR model (1) and VECM model (2) including these events as dummy variables.

The mathematical representation of the VAR model (1) with dummy variables is given by:

$$\Delta P_t = \beta_0 + \beta_1 \Delta P_{t-1} + \cdots + \beta_n \Delta P_{t-n} + dummy1 + dummy2 + \varepsilon_t \tag{3}$$

The mathematical representation of the VECM model (2) with dummy variables is given by:

$$\Delta P_t = \lambda E P_{t-1} + \sum_{i=1}^{n-1} \phi'_{t-i} \Delta P_{t-i} + dummy1 + dummy2 + \varepsilon_t \tag{4}$$

The models in Equations (3) and (4) have prices and the same dummy variables. *Dummy1* considers the effects of the COVID-19 pandemic on the price relationships, which takes the value "1" for the 2020:01–2020:12 periods and "0 "otherwise since the coronavirus patient was first reported in China in late December 2019. *Dummy 2* takes "1" if the data belong to the 2008:09–2009:08 period and "0 "otherwise capturing the impact of the 2008 financial crisis. *Dummy 2* is defined as this period since the bankruptcy of Lehman Brothers occurred on 15 September 2008 (Adrian and Shin 2010) and it is often assumed that the 2008 financial crisis began in September 2008 (Aruga and Kannan 2020).

3.4. Results

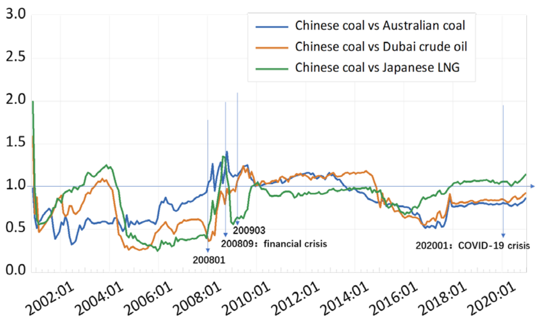
3.4.1. Recursive Cointegration

Figure 3.2 illustrates the results of the recursive cointegration test conducted between the Chinese and international fossil fuel markets. It is observable from Figure 3.2(a) that the Chinese domestic coal price is not cointegrated with the Australian coal and Dubai crude oil markets until January 2008 and March 2009, respectively. On the other hand, the Chinese domestic coal and the Japanese LNG markets were mostly not cointegrated during periods before the 2008 financial crisis but they became cointegrated just before the crisis and again became not cointegrated after the shock from the crisis. These results were also confirmed by Li et al. (2019) showing that the co-movement between the Chinese coal and international energy prices has different trends before and after mid-2008 due to inter-fuel substitution of crude oil and inter-market contagion of the international coal market.

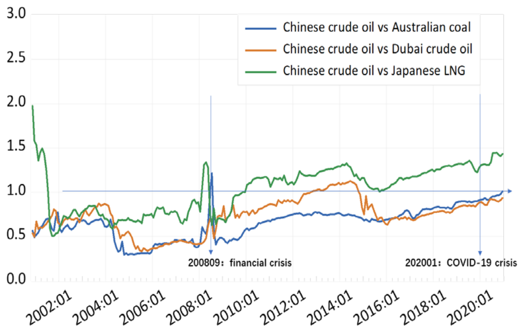
From figure 3.2(a), it is also discernible that the COVID-19 pandemic did not have impacts on the Chinese coal and international fuel market relationships. Both the Australian coal and Dubai crude oil markets continued to have no cointegration relationships with the Chinese coal market and the Japanese LNG market remained to show a cointegration relationship with the Chinese coal market even after the COVID-19 pandemic occurred.

Next, we would like to look into the effects of the two crises on the Chinese crude oil and international fossil fuel market linkages. Figure 3.2(b) suggests that both the relationships between the Chinese crude oil vs the Australian coal and the Chinese crude oil vs the Japanese LNG market received impacts from the 2008 financial crisis since the cointegration relationships have altered before and after the crisis for these relationships. However, the Dubai crude oil market remained to have no cointegration relationship with the Chinese crude oil market during this crisis.

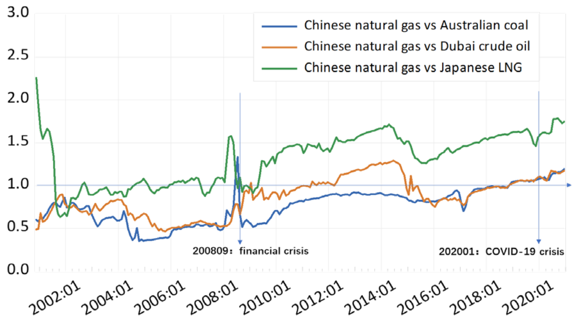
Regarding the COVID-19 shock, none of the relationships between the Chinese crude oil and the international fossil fuel market were influenced by this shock.



(**a**) Chinese coal and International fossil fuel



(**b**) Chinese crude oil and international fossil fuel



(**c**) Chinese natural gas and international fossil fuel

Figure 3.2. Recursive cointegration of Chinese and International fossil fuel prices.

Finally, Figure 3.2(c) illustrates the results of the impacts of the crises on the Chinese natural gas market. Similar to the results of Figure 2b while the relationship between the China natural gas vs the Australian coal and that between the China natural gas vs the Japanese LNG were influenced by the 2008 financial crisis, the relationship between the Chinese natural gas and

Dubai crude oil market did not change during this crisis. The COVID-19 shock also did not show any impact on the Chinese natural gas and international fossil fuel market linkages.

3.4.2. Johansen Cointegration

Table 3.3 illustrates the results of the Johansen test between Chinese fossil fuel and international fossil fuel prices.

Table 3.3 Results of the Johansen cointegration test.

Between Different Market	Rank Number	Trace Statistic	0.05 Critical Value	Max-Eigenvalue Statistic	0.05 Critical Value
Chinese coal vs Australian coal	None *	25.95 *	15.49	21.45 *	14.26
	At most 1 *	4.5 *	3.84	4.5 *	3.84
Chinese coal vs Dubai crude oil	None *	27.65 *	15.49	23.19 *	14.26
	At most 1 *	4.45 *	3.84	4.45 *	3.84
Chinese coal vs Japanese LNG	None *	38.54 *	15.49	35.84 *	14.26
	At most 1	2.69	3.84	2.69	3.84
Chinese crude oil vs Australian coal	None *	23.16 *	15.49	18.81 *	15.49
	At most 1*	4.34 *	3.84	4.34 *	3.84
Chinese crude oil vs Dubai crude oil	None *	23.64 *	15.49	21.45 *	15.49
	At most 1 *	4.5 *	3.84	4.5 *	3.84
Chinese crude oil vs Japanese LNG	None *	39.54 *	15.49	35.65 *	15.49
	At most 1*	3.89 *	3.84	3.89 *	3.84
Chinese natural gas vs Australian coal	None *	28.59 *	15.49	23.55 *	15.49
	At most 1*	5.04 *	3.84	5.04 *	3.84
Chinese natural gas vs Dubai crude oil	None *	26.18 *	15.49	22.68 *	15.49
	At most 1	3.49	3.84	3.49	3.84
Chinese natural gas vs Japanese LNG	None *	45.01 *	15.49	40.81 *	15.49
	At most 1	4.20	3.84	4.20	3.84

Note: * Significant at the 5% significance level.

First, Table 3.3 suggests that the Chinese domestic coal price is not cointegrated with the Australian coal and Dubai crude oil prices during the 2001:01–2020:12 period. The reason for this is perhaps because the Chinese domestic coal price has been controlled by the Chinese government until 2013 (Zhang et al. 2018). In contrast, the Chinese domestic coal market is cointegrated with the Japanese LNG market. This is likely related to China's shift from coal to natural gas to reduce its carbon emission.

Secondly, Table 3.3 indicates that the Chinese crude oil price is not cointegrated with the Australian coal, Dubai crude oil, and Japanese LNG prices. The reason for the Chinese crude oil not having linkages with the international market is perhaps because the crude oil market is still regulated by the government (Lin and Ouyang 2014). For example, the prices of gasoline, diesel, and aviation kerosene are subsidized by the Chinese government.

Thirdly, the Chinese natural gas price is not cointegrated with the Australian coal price, while the Chinese natural gas price is cointegrated with the Dubai crude oil and Japanese LNG prices. This is because China's natural gas is still mainly imported. The imported natural gas prices of the Asian countries are often linked with the Japan Crude Cocktail (JCC) oil price, which represents the average price of Dubai crude oil imported to Japan (Tang and Aruga 2020).

3.4.3. Results of the Impact of both Crises on the Chinese and International Fossil Fuel Market

Table 3.4 shows the impact of the two crises on the Chinese and international fossil fuel markets estimated with the VAR and VECM. These analyses are conducted to see whether the changes in the linkages between the Chinese and international fossil fuel markets are related to the effects of the two crises on the Chinese and international fossil fuel prices.

It is discernible from Table 4 that the shock from the 2008 financial crisis at least became significant in one of the three linkage models in all three Chinese fossil fuel markets where the effect of COVID-19 was only evident in the Chinese natural gas market. Furthermore, comparing the coefficients of the two dummy variables in the Chinese natural gas model, it is evident that the negative shock from the 2008 financial crisis on the Chinese natural gas market was severer than that of the COVID-19.

On the other hand, except for the Australian coal market, none of the coefficients of the international fossil fuel prices in Table 3.4 became significant suggesting that the shocks from the two crises on the linkages between the Chinese and international fossil fuel markets were not influenced by the shocks on the international fossil fuel markets. Even the shock from the 2008 financial crisis found on the Australian coal market is likely related to the effects of the Chinese energy policy since the Chinese government has implemented a 4 trillion yuan ($586 billion) stimulus package during the 2008 financial crisis and that this stimulus package has led China to increase its coal imports from Australia (Yuan, Liu, and Wu. 2010). Hence, it is believable that all the shocks affecting the linkages between the Chinese and international fossil fuel markets are driven by the shocks in the Chinese fossil fuel market.

In sum, the results of Table 3.4 indicate that the linkages between the Chinese and international fossil fuel markets were more severely affected by the 2008 financial crisis compared to the COVID-19 pandemic and both the shocks from the 2008 financial crisis and the COVID-19 pandemic on the linkages are likely driven by the impacts on the Chinese fossil fuel markets.

Table 3.4 Results of the impact of both crises on Chinese and international fossil fuels.

Chinese and International Fossil Fuel	Used Model	Independent Variables	Dummy Variate	Coefficient	t-Value
Chinese coal vs Australian coal	VAR	China coal	dummy1	−0.129 *	−2.994 *
			dummy2	0.036	0.920
		Australian coal	dummy1	−0.160 *	−2.549 *
			dummy2	0.043	0.742
Chinese coal vs Dubai crude oil	VAR	China coal	dummy1	−0.147 *	3.203 *
			dummy2	0.048	1.131
		Dubai crude oil	dummy1	−0.067	−1.291
			dummy2	−0.020	−0.414
Chinese coal vs Japanese LNG	VAR	China coal	dummy1	−0.181 *	−3.890 *
			dummy2	0.037	0.841
		Japanese LNG	dummy1	−0.037	−1.103
			dummy2	0.033	−1.029
Chinese crude oil vs Australian coal	VAR	Chinese crude oil	dummy1	−0.097	−0.925
			dummy2	−0.071	−0.723
		Australian coal	dummy1	−0.145 *	−2.320 *
			dummy2	0.050	0.852
Chinese crude oil vs Dubai crude oil	VAR	Chinese crude oil	dummy1	−0.066	−0.699
			dummy2	−0.036	−0.392
		Dubai crude oil	dummy1	−0.051	−1.014
			dummy2	−0.023	−0.475
Chinese crude oil vs Japanese LNG	VAR	Chinese crude oil	dummy1	−0.208 *	−2.252 *
			dummy2	−0.081	−0.899
		Japanese LNG	dummy1	−0.048	−1.573
			dummy2	−0.044	−1.451
Chinese natural gas vs Australian coal	VAR	Chinese natural gas	dummy1	−0.263 *	−2.194 *
			dummy2	−0.241 *	−2.138 *
		Australian coal	dummy1	−0.162 *	−2.536 *
			dummy2	0.033	0.553
Chinese natural gas vs Dubai crude oil	VECM	Chinese natural gas	dummy1	−0.186	−1.675
			dummy2	−0.193	−1.781
		Dubai crude oil	dummy1	−0.082	−1.552
			dummy2	−0.058	−1.123
Chinese natural gas vs Japanese LNG	VECM	Chinese natural gas	dummy1	−0.304 *	−3.005 *
			dummy2	−0.242 *	−2.421 *
		Japanese LNG	dummy1	−0.048	−1.523
			dummy2	−0.039	−1.243

Note: * Significant at the 5% significance level. Dummy1 is defined as the 2008 financial crisis dummy variable. Dummy2 is defined as the COVID-19 dummy variable.

3.5 Discussion

The results indicate that besides the Chinese fossil fuel and Dubai Crude oil, the cointegration relationships between the Chinese and international fossil fuel markets were changing during the 2008 financial crisis. However, our results suggest that the cointegration relationships between the Chinese and international fossil fuel markets remained unchanged when the COVID-19 pandemic occurred except for the linkages between the Chinese natural gas market vs the Australian coal and Japanese LNG markets.

We believe this difference in the shock on the relationship between the Chinese and international fossil fuel market is due to the different causes and consequences of the crises (Spatt 2020). The 2008 financial crisis reflected infection of the financial system due to excess leverage and poor-quality mortgage loans (Spatt 2020), and this financial behavior is likely to be considered as endogenous structural breaks, which caused immense impacts on energy markets (Aruga and Kannan 2020; Yuan, Liu, and Xie., 2010). Furthermore, since the date of the occurrence of the 2008 financial crisis was uncertain, the energy stakeholders could not expect the timing of the shock, and hence, it is likely that this uncertainty affected the dynamic linkages between the Chinese and international fossil fuel markets.

On the other hand, the COVID-19 pandemic was somewhat predictable and the shock on the financial system was not as severe compared to the 2008 financial crisis. Indeed, even during the COVID-19 pandemic, the world's major stock markets like the Dow Jones and Nikkei 225 index have plummeted briefly but quickly recovered. One likely reason for the financial market to remain stable compared to the 2008 financial crisis during the COVID-19 pandemic is that the causes of the pandemic were clear and the investors were possible to forecast that the economy will recover when the pandemic ends (Jackson et al. 2021). Thus, it is probable that the impact of the COVID-19 on energy markets was somewhat anticipated by the stakeholders and this kept the Chinese coal and crude oil markets to have the same relationship with the international fuel markets.

Although the linkages between the Chinese and international fossil fuel markets were not changing before and after the COVID-19 pandemic, we identified that the incident at least affected negatively on the Chinese natural gas price. This reduced Chinese natural gas price during the COVID-19 pandemic might be reflecting the reduced natural gas demand during the lockdown periods.

6. Conclusions

The study revealed that the cointegration relationships between the Chinese and international fossil fuel markets are affected by the 2008 financial crisis, while the COVID-19 pandemic did not have a clear impact on the relationships. Thus, we identified that the effects of the COVID-19 on the linkages between the Chinese and international fossil fuel markets are not as evident compared to the 2008 financial crisis. As the stock and energy markets are recovering quickly to levels before the COVID-19 pandemic hit the world economy (Höhler and Lansink 2021), the market participants of the Chinese fossil fuel markets were likely able to anticipate the outcomes of the shock of the incident compared to that of the 2008 financial crisis.

These conclusions provide some suggestions regarding risk management and policy recommendations. As we found that the shocks from the 2008 financial crisis and the COVID-19 on the relationships between the Chinese and international energy markets were driven by the effects on the Chinese fossil fuel market, the stakeholders in the Chinese fossil fuel market need to pay more attention to the Chinese fossil fuel market when considering the risk involved in trading between the Chinese and international energy markets. As argued by Chan and Woo (2016), China should consider its domestic fossil fuel market when examining the dynamic relationship between the Chinese and international energy markets suggesting that policymakers should account not only for the dynamics relationships but also attach importance to the dynamic relationship driven by the Chinese fossil fuel market when stabilizing energy prices during the crises.

Our study is limited in the sense that the impact of the recent 2008 financial crisis is only considered in this study. Furthermore, our research may be expanded to involve other global events, such as the 1997 Asian Financial Crisis and SARS.

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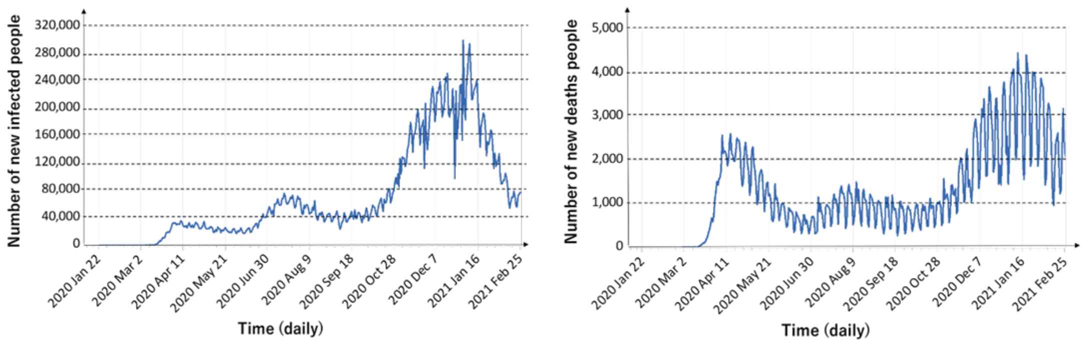
Part 4: The relationship between fossil fuel market and financial market during the COVID-19 pandemic: Evidence from Bayesian DCC-MGARCH models

4.1. Introduction

Since the outbreak of the COVID-19 pandemic, many countries have adopted restrictive measures to prevent the spread of the virus, which has led to the stagnation of many industries and a decrease in the demand and consumption of fossil fuels (Jiang et al., 2021). Global fossil fuel demand fell by 6% in 2020, with the United States (US) and the European Union (EU) reporting the largest fall of 9% and 11%, respectively (IEA, 2020). The reduction in the consumption of fossil fuels is likely to have adverse impacts on fossil fuel prices. Taking the price of the US West Texas Intermediate (WTI) as an example, it dropped below US $20 per barrel, which was the lowest in the past 18 years (Dutta et al., 2020). Meanwhile, Zhang et al. (2020) suggested that the pandemic had a significant impact on the stability of the financial markets. For example, the S&P 500 Index reached 3380.16 points on February 14, 2020, but plunged to 2237.40 on March 23, 2020, which indicated a drop of 30% within one month (Yahoo. finance) as the pandemic started to spread in the US.

We conjecture that, before the pandemic, the relationship between fossil fuel and financial assets was relatively stable. To deal with the risk of fluctuation in the price of fossil fuels, investors in the fossil fuel market would hold assets that are negatively correlated or uncorrelated with the fossil fuel market, such as clean energy stock, gold, and Bitcoin (Al-Yahyaee et al, 2019).



(a): the new cases in the US (b): the new deaths in the US

Figure 4.1: the Covid-19 pandemic condition in the United States.

Note: This figure is created by new cases and deaths data of the US from a database source: Johns Hopkins University CSSE COVID-19 Data, Link: https://github.com/CSSEGISandData/COVID-19

In response to the pandemic, the US implemented lockdown regulations prohibiting people from stepping out. The regulations caused many industries to stagnate and directly affected energy consumption, which lowered the price volatility of the energy market (Jiang et al., 2021). Simultaneously, due to the increasing number of new infections and deaths (see Figure 1), the restrictions also affected investor confidence. The investors began to panic and sold their financial assets (Chang et al., 2020), which further depreciated the prices of those financial assets. Thus, it is probable that both the fossil fuel and financial asset markets were adversely affected by the pandemic (Zhang et al., 2021), and as a result, both markets formed a positive, correlative relationship. Hence, we expect their relationship to differ before and after the crisis. However, if their relationship changes before and after the pandemic, it becomes difficult for investors to manage their portfolios rationally by combining various assets based on modern portfolio theory (MPT) (Ding et al., 2014).

Since Markowitz (1952), MPT has become one of the fundamental pillars of portfolio construction. The MPT assumption is that risk-averse investors can construct a portfolio that minimizes risk, which is calculated by a weighted average related to the correlation coefficients of the returns of its component assets. Thus, it is speculated that the greater the positive correlation of the portfolio, the greater the risk because all the weights in this average are positive values. According to the MPT assumption, Baur and Lucey (2010) proposed the concept that an asset is a haven asset if it is negatively correlated or uncorrelated with another asset during crisis periods and suggested gold as a haven asset for stock markets. Along these lines, Dutta et al. (2020) also suggested gold as a haven asset for oil because there is a significant negative relationship between gold and oil. Bitcoin, however, is not a haven asset for oil because of the positive relationship between Bitcoin and oil during the pandemic. Nonetheless, the MPT assumption is still undermined by crisis. For example, there was a strongly positive cross-market linkage during the 2008 financial crisis period (Ding et al., 2014). Moreover, So et al. (2021) suggested that the diversification effect during a pandemic is weaker than during normal periods due to the co-movement of the cross-financial market triggered by extraordinary events such as a pandemic.

While the linkage between fossil fuels and their hedging assets started drawing attention due to the pandemic, academic research on this issue is insufficient. Hedging between fossil fuel and other assets is important to assure capital for purchasing fossil fuel, which will help stabilize the energy supply. However, events like the pandemic could make it difficult for the suppliers of energy to hedge the risk of changes in the fossil fuel price by combining their portfolios with financial assets such as gold and Bitcoin. Therefore, it is necessary to re-analyze the connection between fossil fuels and their hedging assets for cross-market investors to understand portfolio risk management based on the MPT. This issue is crucial for institutions seeking to assure energy for their citizens because energy markets are often strongly affected by changes in financial markets such as relevant stock and gold markets and hedging across the financial markets is crucial for achieving sustainable energy supply.

If the linkage between the fossil fuel market and its hedging assets is time-varying during the pandemic, investors should pay more attention to the changes in their relationships. For example, it would be worthwhile to note whether the change is from a negative correlation to a positive correlation, from a positive correlation to a negative correlation, or from a strong correlation to a weak correlation. This implies that it is difficult to grasp the specific change to model their variations (risk) over time. In particular, when fossil fuels become positively correlated with clean energy, gold, and Bitcoin during the pandemic, the effect of reducing risk may become very low based on MPT. Hence, investors and policymakers would be expected to account for the dynamic relationship between fossil fuels and its hedging assets during a pandemic. Therefore, our study is expected to provide important information on the dynamic relationship between the energy and financial markets so that the right adjustments can be made to diversifying portfolios after accounting for price fluctuation risk caused by the pandemic. The results of the study can therefore offer a valuable reference to understand how the relationships between the energy and financial markets will be affected by the pandemic.

Although some empirical studies have explored the relationship between oil prices and hedging assets, such as clean stock, gold, and Bitcoin prices separately, to the best of our knowledge, no study has explored the linkage between fossil fuel prices (coal, crude oil, and natural gas) and its hedging assets (such as clean energy stock, gold, and Bitcoin prices) simultaneously during a pandemic.

Therefore, to fill this important gap, the study examines how the relationships among the fossil fuel and financial markets have been affected during the COVID-19 pandemic. For this purpose, the US market was chosen for the following reasons: First, the US has the world's largest energy and financial trading market, and it is important for investors to deepen their understanding of the relationship between the energy and financial markets. Second, the US has one of the largest numbers of COVID-19 patients in the world, which means that the US market can better reflect the impact of the pandemic on the energy and financial markets. In addition, compared to prior studies, which mostly employed the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) or Constant Conditional Correlation (CCC)-GARCH model using the Maximum Likelihood (ML) estimation to test the correlation, our study employs the Bayesian DCC-multivariate GARCH (DCC-MGARCH) models. In the Bayesian DCC-MGARCH models, the standard error of the estimated parameter is smaller than the ML (Shiferaw, 2019) and thus, more accurate for the results of the study.

The clean energy stock, gold, and Bitcoin cryptocurrency markets are chosen as the markets that may have the characteristics of hedging for fossil fuels (Kumar et al., 2019; Reboredo et al., 2017; Gkillas et al., 2020). Gold is usually chosen as a hedging asset to offset the risk that investors face because it is a universal currency recognized all over the world

(Cunado et al., 2019; Lin et al., 2018; Ruan et al., 2018). Bitcoin is a new financial product that may be useful for inclusion in investment portfolios (Henriques and Sadorsky, 2018) because of its popularity as a cryptocurrency. During the pandemic, while demand for fossil fuels has declined, the demand for clean energy has risen accordingly (Wan et al., 2021), which means that the clean energy stock market has attracted more private capital reallocation (Reboredo et al., 2017) as clean energy is now considered the most efficient alternative to meet fossil fuel consumption (Baz et al., 2021). Thus, it is reasonable to assume that clean energy stocks might be regarded as a good hedge asset during the pandemic.

As the world still heavily relies its energy on fossil fuels, countries need to hedge the risk of sudden price change for sustainable energy supply. To mitigate such risk, energy suppliers need to hedge across the financial markets since energy prices are often affected by financial markets. Since the COVID-19 had devastating impacts on fossil fuel and financial markets, the current study seeks how susceptible the relationships among the fossil fuel and financial markets are during this pandemic to provide important information to cope with potential risks that might have similar impacts on the relationships in the future.

In the next section, the related prior literature is discussed. The third section describes the data and methods. The fourth section explains the results of the analysis. The final section discusses the implications of the results and draws conclusions.

4.2 Previous Research

We present our review of previous studies from four aspects: the nexus between the fossil fuel and financial markets; whether bitcoin and gold are safe havens against the crude market; whether the COVID-19 pandemic affected the fossil fuel market and financial market such as gold, clean energy stock, bitcoin; studies applying the DCC-GARCH model. A summary of relevant studies introduced in this study is shown in Table 4.1.

Table 4.1. Publication year, authors, type of study, and approach of relevant literature.

Publication year	Authors	Type of study	Approach
2014	Fioruci, Ehlers, and Louzada	Studying an implementation of Multivariate GARCH DCC Models by Bayesian estimation	DCC-MGARCH model with Bayesian estimation
2017	Reboredo et al	Studying co-movement and causality between oil and renewable energy stock prices	continuous wavelets and cross-wavelet transforms
2019	Shiferaw	Studying the application of Bayesian DCC-MGARCH to agricultural and energy markets	DCC-MGARCH model with Bayesian estimation
2019	Al-Yahyaee et al	Studying the volatility and correlation between Bitcoin and oil and international commodity markets	DCC-GARCH model

2020	Chang et al	Examining Herding behavior in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19	the cross-section Standard Deviation (CSSD) and the cross-section Absolute Deviation (CSAD) measures
2020	Das et al	Studying whether Bitcoin and gold are safe havens against crude oil	a dummy variable GARCH and quantile regression model
2020	Kyriazis	Studying whether Bitcoin and gold are safe havens against other markets	DCC-GARCH model
2020	Kanamura	Studying the correlations between clean energy indices and energy commodities	supply and demand-based correlation model, DCC-GARCH
2021	Moussa et al	Studying the dynamic relationship between Bitcoin and fossil fuel markets in the short and long-run over the period 2011–2018	Smooth Transition Error Correction Model (STECM)
2021	Rehman and Kang	Studying causality relationship between Bitcoin and energy commodity markets	Maximal overlap discrete wavelet transformation (MODWT), and nonlinear causality
2021	Hoang et al	Examining how the impact of the COVID-19 pandemic on the global energy market	Review by previous literature and data related to energy market
2021	Heinlein et al	Examining the relationship between crude oil and stock market returns during Covid-19 crisis	multiplicative component GARCH
2021	Hammoudeh et al	Examining the causal relationship between oil prices returns and clean energy stock market during the COVID-19 pandemic.	Unit root-in-quantiles test and nonparametric quantile causality test
2021	Baz et al	Studying the nexus between fossil fuel, renewable energy, and economic growth	nonlinear autoregressive distributed lag (ARDL) model
2021	Wan et al	Examining the impact of the COVID-19 pandemic on investment in clean energy versus the fossil fuel stock market in China	Regression modeling method by relevant variable
2021	Tang and Aruga	Studying how the impact of the COVID-19 pandemic and 2008 financial crisis on China and international fossil fuel	Vector Autoregressive (VAR) model including Dummy variable
2021	Shehzad et al	Examining how the impact of COVID-19 on stock markets from a comparative analysis of an asymmetric volatility spillover between China and Pakistan	the bivariate VAR-DCC – Exponential GARCH (EGARCH) model
2021	Chevallier	Studying how the correlations between the macro-financial	Dynamic Conditional Correlation with

		environment and CO2 emissions in the aftermath of the COVID-19 diffusion	Mixed Data Sampling (DCC-MIDAS)
2021	Sayed and Eledum	Studying how the short - term response of the Saudi stock market (Tadawul) to the COVID - 19 outbreak	Event study methodology

Some studies have attempted to investigate the nexus between clean energy and fossil fuels, such as the causality between oil and renewable energy stock prices (Reboredo et al. 2017) and the relationship between fossil fuels, renewable energy, and economic growth in Pakistan (Baz et al. 2021). In addition, there is a growing body of literature on the relationships between Bitcoin and fossil fuel markets. For example, Moussa et al. (2021) investigate their relationship in a dynamic aspect from the short and long-run over the period 2011–2018 using the STECM approach. The study reveals that the impact of Bitcoin on fossil fuel lagged values is positive, while Rehman and Kang (2021) employ the MODWT approach to test their time-frequency co-movement and causality relationship to suggest that while both oil and gas have a significant co-movement with the Bitcoin returns, it no longer exhibits a co-movement when the effect of coal market is considered.

Other studies have investigated the relationship between crude oil, Bitcoin, and gold from a finance perspective. For instance, using the DCC-GARCH model, Al-Yahyaee et al. (2019) suggested that Bitcoin and gold assets have diversification and hedging properties for S&P Goldman Sachs Commodity Index investors. Conversely, using a dummy variable GARCH and a quantile regression model, Das et al. (2020) showed that 1) Bitcoin is not a superior asset over others in hedging oil-related uncertainties, and 2) the hedging capacity of different assets is conditional upon the nature of the oil risks and market situation. Moreover, using methodologies of DCC and wavelet coherence, Kyriazis (2020) indicated that Bitcoin had a long way to go before it can be considered a safe-haven asset like gold. From the results of the studies above, we can conclude that it is uncertain whether Bitcoin is a hedging asset for crude oil and that gold is a haven asset in different periods.

Among the studies investigating the impact of the COVID-19 on fossil fuel and financial markets, Wan et al. (2021) conducted a study on the impact of the crisis on investment in clean energy versus the fossil fuel stock market in China. They find evidence that the pandemic is causing impacts on the clean energy and fossil fuel markets. Hoang et al. (2021) suggest that while the COVID-19 pandemic affected the fossil fuel market the most, the clean energy market was also not spared. Even after the outbreak, there is a controversy regarding whether clean energy can replace fossil fuels as the economic and environmental impact need to be considered for investment in renewable energy to replace fossil fuels (Kanamura, 2020). According to Kanamura [28], the clean energy business might represent a form of environmental value, while fossil fuels might represent economic value. It is also known that all renewable energy stock markets are affected by the volatility of the US fossil fuel energy prices due to COVID-19 (Chang et al. 2020).

In addition to the prior studies on the impact of COVID-19 on stock related to clean energy, there are also studies on stock indices and industry stocks during COVID-19. For example, Shehzad et al. (2021) utilized VAR-DCC-EGARCH to test the volatility spillover between the stock market and reported a volatility spillover for both China and Pakistan stock markets during the pandemic. Sayed and Eledum (2021) used event study methodology to suggest that when the announcement of the COVID-19 went in after 9 days, it only had a negative and significant effect Saudi stock market and has different effects on different industries such as banks, consumer services, capital goods, and transportation.

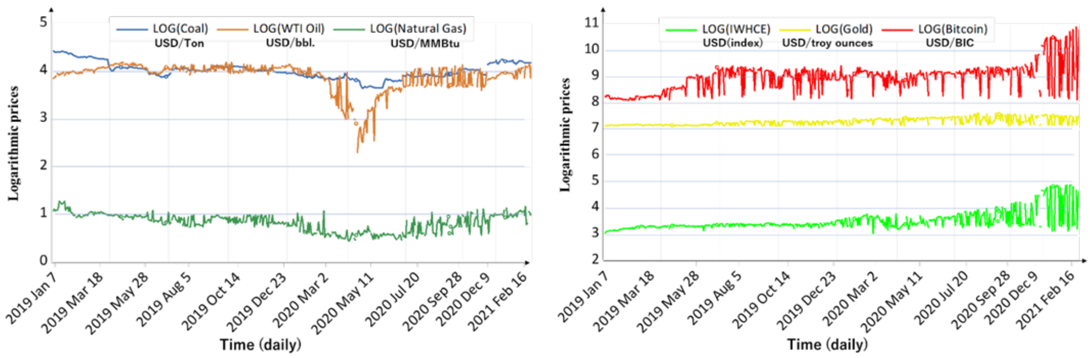
However, these studies above did not investigate whether the correlation between clean energy and fossil fuels became any stronger during the pandemic. Moreover, Heinlein et al. (2021) apply the multiplicative component GARCH model to investigate how the relationship between crude oil and stock markets, suggesting that there are correlations between the crude oil and stock markets for all countries during the COVID-19 crisis. The authors also indicate that the stock markets of commodity exporters have stronger correlations with oil returns than their importing counterparts. Hammoudeh et al. (2021) explore the causal relationship between oil prices and clean energy based on the nonparametric causality-in-quantiles, indicating the oil price returns have an absence of significant causal relationships with clean energy stock during the COVID-19 pandemic period. Tang and Aruga (2021) suggest that there exists an impact from the COVID-19 pandemic on the relationship between China and international fossil fuel and that the changes in the relationship are driven by the influence of the pandemic on the Chinese fossil fuel market. Besides, Chevallier (2021) indicates that the COVID-19 confirmed cases and deaths have an adverse influence on CO2 emissions.

Finally, the Bayesian DCC-MGARCH method was first proposed by Fioruci, Ehlers, and Louzada (2014). Then, this method was applied by Shiferaw (2019) to study the time-varying correlation between agricultural commodities and energy prices in comparison with ML methods. Shiferaw (2019) showed that the posterior standard deviations of the parameters generated by the Bayesian DCC-MGARCH models were slightly lower than the standard deviations of the parameters from ML. These results indicate that the Bayesian inference process might be better than the conventional ML approach for estimating parameters in the DCC-MGARCH models. Compared to the above previous literature, our current study explores how these relationships among fossil fuel, bitcoin, gold, clean energy stock markets are changing during the COVID-19 pandemic periods using the Bayesian DCC-MGARCH model.

4.3. Data

The daily returns of the US fossil fuel market (Coal, WTI crude oil, and Henry Hub Natural Gas) and Invesco Wilder Hill Clean Energy (IWHCE) Index are the samples analyzed in this study from January 2, 2019 to February 26, 2021. The IWHCE Index is not directly available, so our study uses the clean energy Exchange-Traded Fund as a proxy variable because the fund is based on the IWHCE Index, which is computed by the stocks of US publicly traded companies engaging in the business of advancing clean energy and conservation (Invesco, 2021). The daily prices of these samples related to US energy are the official close prices sourced from INSIDER (2021). The daily gold data comes from GOLDHUB (2021), and the price unit is US dollars per troy ounce. The Bitcoin daily prices are obtained from Yahoo Finance (2021) and are quoted as US dollars. Since the energy markets and financial markets mentioned above have different calculation units, we take the data logarithmically, as shown in Figure 2.

The DCC-MGARCH models require price returns data; therefore, the percentage of continuously compounded returns r_t is computed by $r_t = 100 \times [\ln(p_t) - \ln(p_{t-1})]$, where p_t denotes the US fossil fuel, IWHCE, gold, and Bitcoin prices in period t. Figure 3 shows the plot of price returns against time.



(a) the logarithmic prices of fossil fuel **(b) the logarithmic prices of financial variable**

Figure 4.2: the related variables being studied between 3 January 2019 and 26 February 2021

Notes: IWHCE: Invesco Wilder Hill Clean Energy ; WTI: West Texas Intermediate

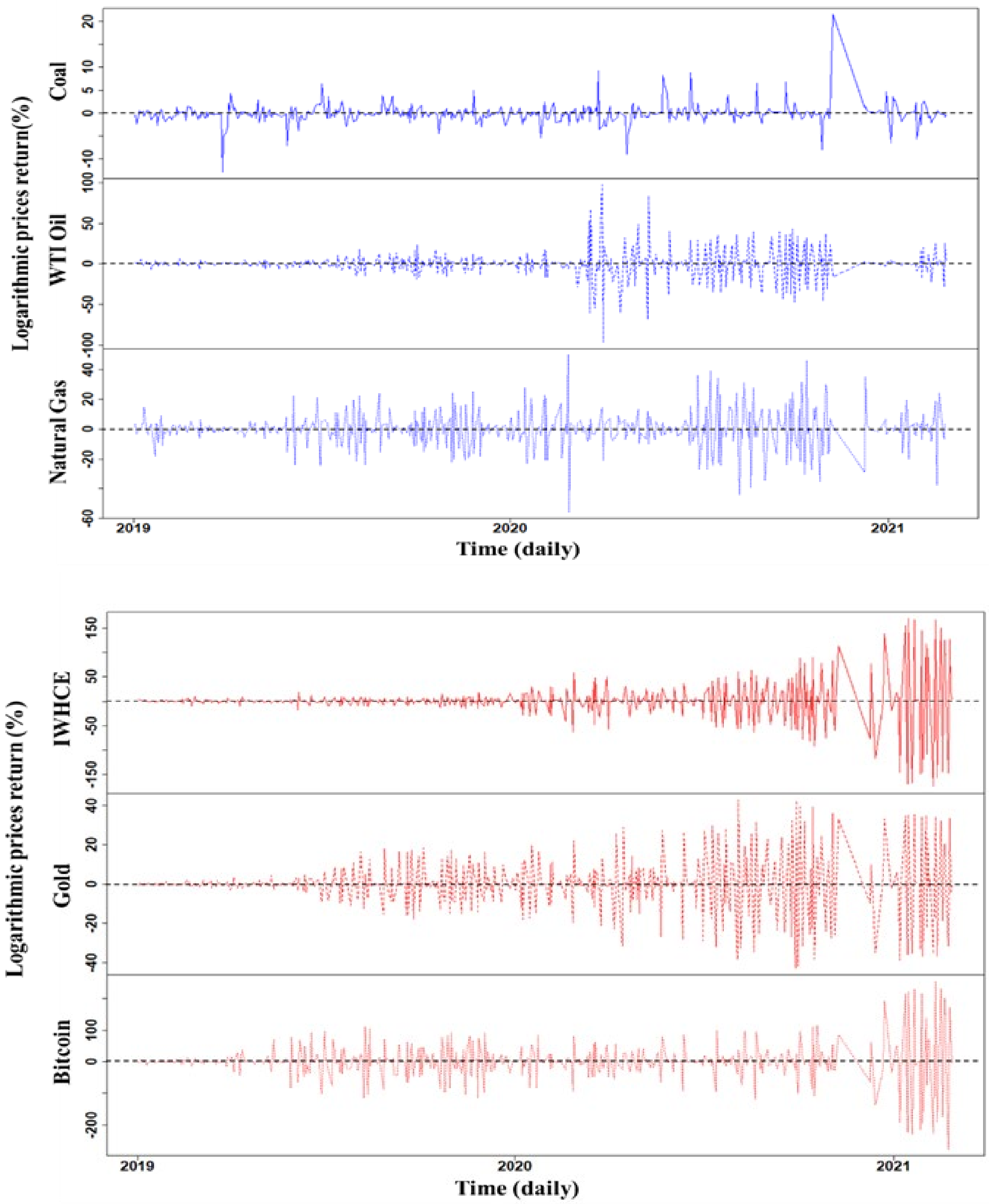


Figure 4.3. The US fossil fuel, IWHCE, Gold, and Bitcoin price return series. Source: Own calculation. Notes: IWHCE: Invesco Wilder Hill Clean Energy; WTI: West Texas Intermediate

4.4 Methods

According to the MPT presented in the introduction, we investigated the correlations among the fossil fuel and IWHCE, Gold, and Bitcoin price returns for analyzing how the portfolio investment has been affected during the COVID-19 pandemic. To this end, we used the DCC-MGARCH model with Bayesian estimation. In the Bayesian DCC-MGARCH model framework, we present our methods in three steps: the MGARCH model, the Bayesian estimation of the models, and estimating the posterior distribution using Markov Chain Monte Carlo (MCMC). The summary of the steps is shown in Figure 4.4.

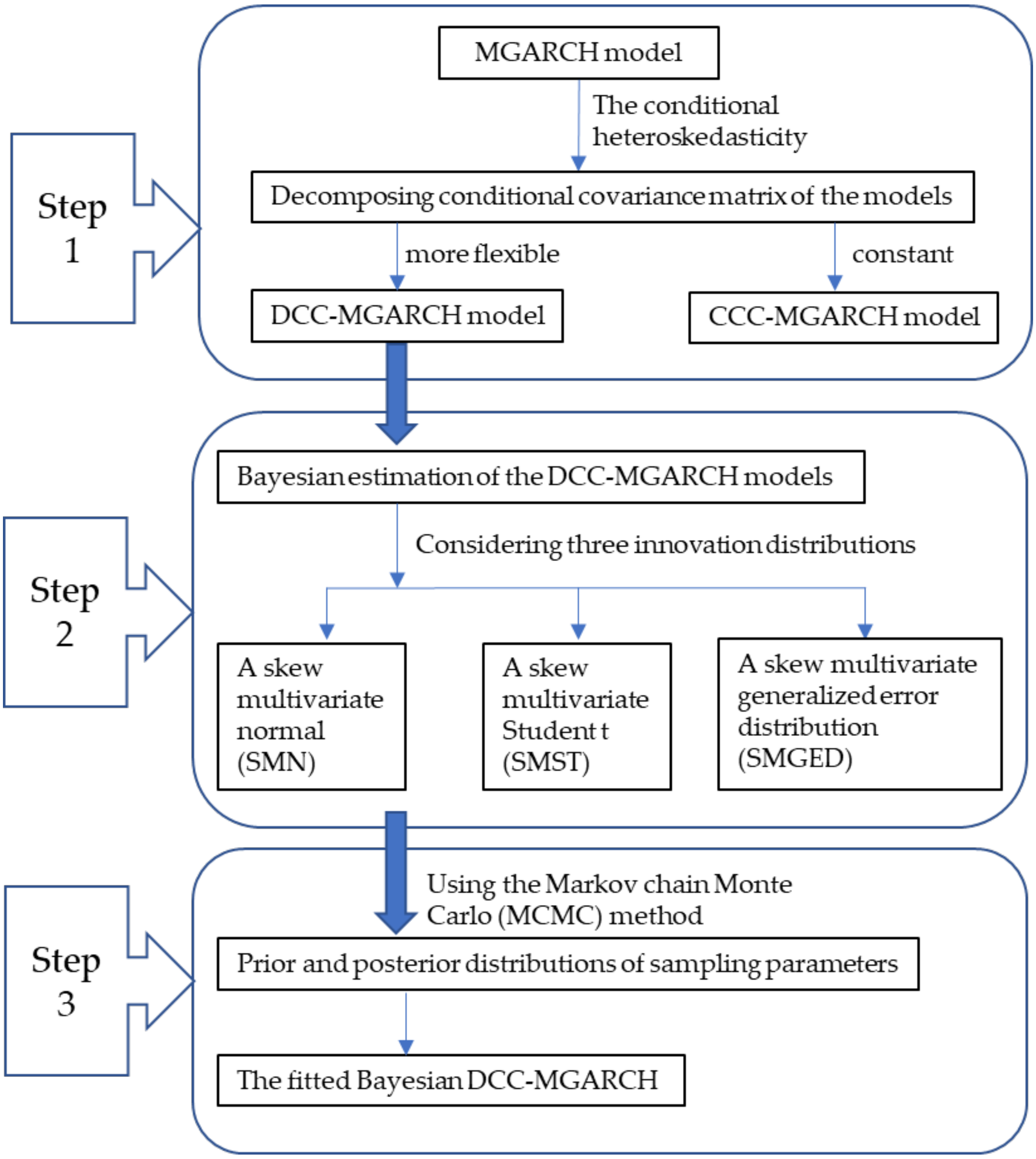


Figure 4.4: the framework of methodology. Source: Own drawing.

4.4.1 *DCC-MGARCH Models (step 1)*

We employ the DCC-MGARCH model to study the connectedness of fossil fuel and IWHCE, gold, bitcoin market during the COVID-19 period. The MGARCH model is developed by many researchers with the examples of Engle and Sheppard (2001), Bauwens et al. (2006), Silvennoinen and Teräsvirta (2009), and Tsay (2010). Due to the MGARCH model is the conditional heteroskedasticity, the conditional covariance matrix of the models can be decomposed into conditional standard deviations and a conditional correlation Matrix. Moreover, the conditional correlation can be assumed to be constant and dynamic over time.

If the conditional correlation is constant over time and only the conditional standard deviation is time-varying, the model is to be the CCC-MGARCH model introduced by Bollerslev (1990). However, it is believed that the assumption of the conditional correlation constant overtime is not always reasonable based on a lot of empirical applications such as Dutta et al (2020a) and Shiferaw (2019). Moreover, Shiferaw (2019) suggests that the DCC-MGARCH is flexible enough to examine the co-movements between different energy and financial market. Thus, the DCC-MGARCH model is applied in our study.

According to Engle and Sheppard (2001), the DCC-MGARCH model is defined as:

$$P_t = \mu_t + r_t \tag{1}$$

$$r_t = {H_t}^{1/2} Z_t \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

where P_t is a $n \times 1$ vector of log prices of n prices at time t, μ_t is a $n \times 1$ vector of the expected value of P_t, r_t is a $n \times 1$ vector of mean-corrected returns of n assets at time t with $E[r_t] = 0$, $\mathrm{Cov}[r_t] = H_t$. H_t is a $n \times n$ conditional variance matrix of return r_t and ${H_t}^{1/2}$ is obtained by a Cholesky factorization of H_t, Z_t is a vector of identically independently distributed (iid) errors with $\mathrm{E}(Z_t) = 0$ and $E(Z_t {Z_t}') = I$. D_t is a $n \times n$ diagonal matrix of standard deviations of return r_t. R_t is the time-varying correlation matrix. The analysis of detailed decomposing is as follows:

First, the diagonal matrix D_t in equation (3) is specified as a univariate GARCH model, and given by:

$$D_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22,t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{nn,t}} \end{bmatrix}$$

Where $h_{ii,t}$ is conditional covariance. Here we specify a GARCH (p, q) model for each conditional covariance $h_{ii,t}$, which can be written as:

$$h_{ii,t} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} r_{i,t-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{ii,t-q}\ , \ i = 1, 2, \ldots, n \tag{4}$$

with $\omega_i > 0, \alpha_i \geq 0, \beta_i \geq 0, \sum_{q=1}^{Q_i} \alpha_{iq} + \sum_{p=1}^{P_i} \beta_{ip} < 1$. Note that the subscripts p and q are the lag lengths. The GARCH model is not limited to the standard GARCH (p, q) models and is often the simplest model GARCH(1,1), which is adequate when p is 1 and q is 1.

Next, the time-varying conditional correlation R_t in equation (3) is the symmetric matrix :

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & 1 \end{bmatrix}$$

Then, the elements of $H_t = D_t R_t D_t$ could be expressed as follows:

$$[H_t]_{ij} = \sqrt{h_{iit}h_{jjt}}\,\rho_{ij,t} \tag{5}$$

where $\rho_{ij,t}$ is a time-varying conditional correlation between returns series i and j. If and only if $h_{iit} > 0$, we can know that H_t is positive definite and R_t is positive definite.

Finally, the proposed symmetric dynamic correlation structure is:

$$Q_t = (1 - a - b)\bar{Q} + a\mu_{t-1}\mu'_{t-1} + bQ_{t-1} \tag{6}$$

$$R_t = Q_t^{*-1}Q_tQ_t^{*-1} \tag{7}$$

where $\bar{Q} = Cov[\mu_t\mu'_t] = E[\mu_t\mu'_t]$ is the unconditional covariance matrix of the standardized errors μ_t. In addition to the conditions for the univariate GARCH model to ensure positive unconditional variances, the parameters a and b are $a \geq 0$, $b \geq 0$, and $a + b < 1$. The Q_t^* is a diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & 0 & \cdots & \sqrt{q_{nnt}} \end{bmatrix}$$

Hence, the typical element of R_t will be of the form $\rho_{ij,t} = \frac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}}$.

4.4.2 Bayesian estimation of DCC-MGARCH models(step 2)

4.4.2.1 Multivariate Skew Densities

To estimate the parameters of the DCC-MGARCH model, the Bayesian approach is used. The Bayesian approach that skewed distributions of the errors should be taken into account in calculating the parameters process because there is potential skew in financial time series (Fioruci, Ehlers, and Louzada. 2014). Therefore, for the distributions of the errors Z_t in equation (2), we consider three different innovation distributions: a skew multivariate normal (SMN), skew multivariate Student t (SMST) (Fiorentini et al. 2003), and skew multivariate Generalized Error Distribution (SMGED) (Kotz and Nadarajah 2004) to fit Bayesian DCC-MGARCH.

According to Kotz and Nadarajah (2004), the multivariate skewed densities can be written as:

$$s(x|\gamma) = 2^k\left(\prod_{i=1}^{k}\frac{\gamma_i}{1+\gamma_i^2}\right)f(x^*),\ \ i = 1, \ldots, k \tag{8}$$

where $f(x^*)$ is a symmetric multivariate density, $x^* = (x_1^*, \ldots, x_k^*)$, $\gamma = (\gamma_1, \ldots, \gamma_k)$, $x_i^* = x_i/\gamma_i$ if $x_i \geq 0$ and $x_i^* = x_i\gamma_i$ if $x_i \leq 0$. $\gamma_1, \ldots, \gamma_k$ is a shape parameter to judge the class of skewed distributions, if the values of γ_i is 1 ($\gamma_i = 1$), the density distributions would be symmetric, and the values of $\gamma_i > 1$ ($\gamma_i < 1$) indicate right (left) skewness. It also can be used to compute the mean μ_{γ_i} and variance $\sigma^2_{\gamma_i}$. The details of the calculations are explained in Fioruci, Ehlers, and Louzada (2014)

Given the extra degrees of freedom parameter ν to equation (8), the SMST has density functions given as follows:

$$s(x|\gamma,\nu) = 2^k\left(\prod_{i=1}^{k}\frac{\gamma_i\sigma_{\gamma_i}}{1+\gamma_i^2}\right)\frac{\Gamma\left(\frac{\nu+k}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)[\pi(\nu-2)]^{\frac{k}{2}}}\left[1+\frac{x^{*'}x^*}{\nu-2}\right]^{-\frac{\nu+k}{2}}, \quad i = 1,\dots,k \tag{9}$$

where $x_i^* = (x_i\sigma_i + \mu_{\gamma_i})/\gamma_i$ if $x_i \geq -\mu_{\gamma_i}/\sigma_{\gamma_i}$ and $x_i^* = (x_i\sigma_i + \mu_{\gamma_i})\gamma_i$ if $x_i \leq -\mu_{\gamma_i}/\sigma_{\gamma_i}$.

Moreover, if the parameter ν is to be ∞ ($\nu \to \infty$) in equation (8), we would obtain the SMN density.

Finally, the SMGED is also known as multivariate exponential power distribution. Its density function can be written as:

$$s(x|\delta) = 2^k\left(\prod_{i=1}^{k}\frac{\gamma_i\sigma_{\gamma_i}}{1+\gamma_i^2}\right)\left[\frac{\Gamma\left(\frac{3}{\delta}\right)}{\Gamma\left(\frac{1}{\delta}\right)}\right]^{\frac{k}{2}}\frac{1}{\left[2\,\Gamma\left(\frac{(\delta+1)}{\delta}\right)\right]^k}exp\left\{-\left[\frac{\Gamma\left(\frac{3}{\delta}\right)}{\Gamma\left(\frac{1}{\delta}\right)}\right]^{\frac{\delta}{2}}\sum_{i=1}^{k}|x_i|^\delta\right\} \tag{10}$$

$$i = 1,\dots,k$$

where δ is a common tail parameter, $x_i^* = (x_i\sigma_i + \mu_{\gamma_i})/\gamma_i$ if $x_i \geq -\mu_{\gamma_i}/\sigma_{\gamma_i}$ and $x_i^* = (x_i\sigma_i + \mu_{\gamma_i})\gamma_i$ if $x_i \leq -\mu_{\gamma_i}/\sigma_{\gamma_i}$.

Therefore, if the errors Z_t in equation (2) are assumed to be SMN, there would be no extra parameter to be estimated. However, the extra degrees of freedom parameter ν will be estimated (Fiorentini et al. 2003) when the errors Z_t is SMST, and the extra parameter δ will be calculated when the errors Z_t is SMGED.

4.4.3 Estimating the posterior distribution (step 3)

4.4.3.1 Prior and posterior Distributions

According to the equation (4), (9), and (10), the set of all model parameters of interest is represented by $\theta = (\omega_i, \alpha_i, \beta_i, \nu, \delta, \gamma_i)$. Following the Bayesian theory, these parameters need to specify the prior distributions and are assumed to be a priori independent and normally distributed. First, according to Ardia (2006), the prior distributions of parameters $\omega_i, \alpha_i,$ and β_i are given by $\omega_i \sim N(u_{\omega_i}, \sigma^2_{\omega_i})I_{(\omega_i>0)}$, $\alpha_i \sim N(u_{\alpha_i}, \sigma^2_{\alpha_i})I_{(0<\alpha_i<1)}$ and $\beta_i \sim N(u_{\beta_i}, \sigma^2_{\beta_i})I_{(0<\beta_i<1)}$, $i = 1,\dots,k$. Secondly, the prior distributions of the tail parameter are assumed as $\nu \sim N(u_\nu, \sigma^2_\nu)I_{(\nu>2)}$ or $\delta \sim N(u_\delta, \sigma^2_\delta)I_{(\delta>0)}$ when the error is SMST or SMGED. Finally, for the skewness parameters, γ_i is set to be $\gamma_i \sim N(0, 0.64^{-1})$ based on Fioruci, Ehlers, and Filho. (2014). Moreover, the Markov chain Monte Carlo (MCMC) method in the framework of Bayesian Inference was used to obtain samples from the joint posterior distributions. The Metropolis-Hastings algorithm is applied to provide the easiest sampling.

4.4.3.2 The performance of the fitted Bayesian DCC-MGARCH

Because three different innovation distributions are considered to fit Bayesian DCC-MGARCH, we applied the three criteria of Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Deviance Information Criterion (DIC) to choose the best fitted DCC-MGARCH model. The model with smaller values of AIC, BIC, and DIC is a way to determine the best fitted DCC-MGARCH models.

It is essential to realize the statistical characterization for the fossil fuel and clean energy, gold, and bitcoin price returns series before the fitted DCC-MGARCH model. On the one hand, to avoid pseudo-regression problems, the idea is to use the Augmented Dickey-Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to identify the stationarity of our test variables. On the other hand, we used the Shapiro-Wilk (SW) and Jarque-Bera (JB) test to detect the sample distribution and skewness, and kurtosis. Moreover, Engle's Lagrange multiplier(LM) test is applied to identify the effects of autoregressive conditional heteroscedastic(ARCH) for each of the returns.

The Shapiro-Wilk (SW) test is published by Shapiro and Wilk (1965) to test the null hypothesis that a sample $r_1, \dots, r_t$ came from a normally distributed population. Its statistic is defined as $SW = \frac{\left(\sum_1^t a_t r_{min}\right)^2}{\sum_1^t (r_t - \bar{r})^2}$, where r_{min} is the smallest return in the sample; $\bar{r}$ is the sample mean; a_t are the coefficients, it is given by : $(a_1, \dots, a_t) = \frac{E^T V^{-1}}{C}$, where C is a vector norm: $C = (E^T V^{-1} V^{-1} E^T)^{1/2}$ and the vector $E^T = (E_1, \dots, E_t)^T$ is made of the expected values of variables sampled from the standard normal distribution; finally, V is the covariance matrix of those normal order statistics.

The Jarque-Bera (JB) test is a goodness of fit test that determines whether or not sample data have skewness and kurtosis that matches a normal distribution. The test is proposed by Jarque and Bera (1980). The JB can be calculated as follows: $\mathrm{JB} = \frac{T}{6}(S^2 + \frac{1}{4}(K-3)^2)$, where T is the number of observations, K represents kurtosis and S represents skewness. The value of JB is a positive number and if it is far from zero, it would indicate that the sample data does not have a normal distribution.

4.5. Result

4.5.1 Descriptive summary of all prices and return series data

Table 4.2 presents the unit root test for all the prices and returns series data. The unit root test of the price series is not exogenous when the p test is applied. The ADF, PP, and KPSS test results in Table 4.2 show that the null hypothesis of non-stationarity is rejected at a 5% level of significance in each of the returns series, but each of the price series becomes stationary from the first difference.

Table 4.2: Unit root tests.

Variables	Level data (t-value)						First difference data		
	ADF return	PP return	KPSS return	ADF price	PP price	KPSS price	ADF price	PP price	KPSS price
Coal	-6.46*	-13.20*	0.18	-2.65	-2.65	0.90*	-18.54*	-18.56*	0.18
WTI (Oil)	-7.03*	-33.75*	0.10	-1.68	-2.32	1.14*	-5.36*	-62.77*	0.12
Natural Gas	-9.72*	-34.17*	0.04	-2.49	-0.82	1.01*	-12.45*	-78.45*	0.09
IWHCE	-10.24*	-43.01*	0.03	-2.12	-3.73	1.54*	-4.95*	-41.75*	0.22
Bitcoin	-10.68*	-41.15*	0.04	-0.34	-5.87	1.46*	-6.73*	-41.78*	0.33
Gold	-10.05*	-41.92*	0.01	-1.57	-0.43	2.56*	-8.58*	-41.93*	0.23

Note: *Denotes statistical significance at the 5% level.

Table 4.3: Statistical properties of fossil fuel and clean energy, Bitcoin and gold market returns

Return Variables	Min.	Max.	Std.	Skewness	Kurtosis	JB	SW	LM
Coal	-12.86	21.51	2.14	2.02	27.28	14585.19 **	0.74 **	3235.64 **
WTI (Oil)	-96.46	97.55	16.43	0.10	8.66	1443.89 **	0.80 **	511.47 **
Natural Gas	-55.89	49.90	11.96	-0.05	3.23	201.69 **	0.91 **	251.66 **
IWHCE	-175.15	169.38	39.19	-0.10	8.09	1258.96 **	0.71 **	104.39 **
Bitcoin	-277.00	254.79	57.40	-0.03	6.41	789.99 **	0.82 **	118.43 **
Gold	-42.67	42.80	13.58	-0.02	1.98	75.80**	0.89 **	105.60 **

Note: **Denotes statistical significance at the 1% level.

Table 4.3 presents the results of summary statistics. The JB statistic is statistically significant at the 1% level, indicating that all the returns series have skewedness and excess kurtosis.

Moreover, the SW statistic is also statistically significant at the 1% level, which indicates that the returns series do not come from a normally distributed population. Thus, according to the SW and JB statistics, all return series are violations of normality assumptions. This implies that it is necessary to consider their asymmetric distributions. Moreover, the results of Engle's Lagrange multiplier (LM) test are statistically significant at the 1% level, which indicates that autoregressive conditional heteroscedastic (ARCH) effects exist for all returns series. As a result, there are three possible Bayesian DCC-MGARCH (1,1) models to be fitted using the SMN, SMST, and SMGED as innovations.

4.5.2 Bayesian estimation of the Dynamic Conditional Correlation-multivariate Generalized Autoregressive Conditional Heteroskedasticity (1,1) model

For the MCMC method in the framework of Bayesian inference (Fioruci, Ehlers, and Filho. 2014), we ran 10,000 iterations with a burn-in phase of 1,000 and a thinning interval of 10 in the MCMC sampling. The remaining 9,000 samples generated from the posterior distribution were kept for the estimation of each parameter sample.

Table 4.4 reports the results of the information criteria of the AIC, BIC, and DIC, which are to identify the goodness of fit statistics for the Bayesian DCC-MGARCH (1,1) models with the SMN, SMST, and SMGED errors. As seen in Table 4.4, the values of the AIC, BIC, and DIC are the smallest for all return and bivariate series under the SMGED, which indicates that the Bayesian DCC-MGARCH model with SMGED errors provided a better fit compared to other models (Fioruci, Ehlers, and Filho., 2014). This is because it is more likely to capture the fat tails and skewed features present in the prices of clean energy stocks, Bitcoin, and gold (Shiferaw, 2019).

Table 4.5 shows the results of the DCC-MGARCH (1,1) model with the SMGED errors for all returns based on Bayesian estimation by the MCMC method. The table consists of the posterior means, medians, and standard deviation with 2.5% to 97.5% credible intervals. First, according to the 95% credible intervals, the estimated posterior densities of the skewness parameters $\hat{\gamma_i}$ are statistically significant because their mean is included in the 95% credible intervals. According to Fioruci, Ehlers, and Filho. (2014), these results provide strong evidence of asymmetry for all returns. Next, the conditional variance parameters a and b are statistically significant at 95% credible intervals, while the values of $a + b$ are less than 1, which indicates the existence of GARCH effects for all returns (Katzke, 2013). Finally, the extra parameter δ also statistically and significantly implies that the model with the SMGED is applicable.

Table 4.6 reports the Bayesian DCC-MGARCH (1,1) model with the SMGED errors for the bivariate combinations of the returns of clean energy, Bitcoin, and gold. As seen from the tables, it is easy to confirm that all estimated parameters are significant at 97.5% credible intervals. Based on parameters a and b results, the CCC model hypothesis ($a = b = 0$) is rejected, indicating that the DCC parameters a and b are satisfied with the model. Moreover, it is easy to calculate that the values of $a + b$ in all bivariate models are less than 1, which implies that the time-varying conditional correlations measured by the Bayesian DCC-MGARCH model with the SMGED are credible.

Table 4.4: Information criteria for all returns and bivariate under the SMN, SMST, SMGED.

	Cri.	SMN	SMST	SMGED		Cri.	SMN	SMST	SMGED
All return	AIC	19007.3	18308.7	18193.7	Coal vs Oil	AIC	5338.7	4962.1	4889.8
	BIC	19114.5	18420.0	18305.0		BIC	5379.9	5007.5	4935.2
	DIC	18984.8	18284.0	18173.0		DIC	5324.2	4947.3	4878.8
Coal vs Natural gas	AIC	5365.9	4988.4	4932.9	Oil vs Natural gas	AIC	6652.2	6453.5	6432.3
	BIC	5407.2	5033.8	4978.2		BIC	6693.4	6498.9	6477.6
	DIC	5354.6	4974.1	4924.5		DIC	6641.7	6439.7	6418.9
Coal vs IWHCE	AIC	5677.2	5368.2	5296.8	Coal vs gold	AIC	5176.4	4889.7	4769.7
	BIC	5718.4	5413.5	5342.2		BIC	5217.6	4935.0	4815.1
	DIC	5662.6	5354.9	5284.2		DIC	5161.6	4875.7	4755.8
Oil vs IWHCE	AIC	6917.2	6825.1	6765.1	Oil vs gold	AIC	6366.0	6288.8	6186.8
	BIC	6958.4	6870.5	6810.4		BIC	6407.2	6334.1	6232.1
	DIC	6906.3	6813.0	6752.7		DIC	6353.9	6277.8	6175.0
Natural gas vs IWHCE	AIC	6916.1	6784.1	6752.8	Natural gas vs gold	AIC	6415.7	6323.0	6263.4
	BIC	6957.3	6829.5	6798.2		BIC	6457.0	6368.3	6308.7
	DIC	6904.9	6771.8	6741.8		DIC	6404.9	6311.7	6252.1
Coal vs bitcoin	AIC	6611.0	6207.0	6075.4	IWHCE vs gold	AIC	6434.2	6368.1	6329.3
	BIC	6652.3	6252.4	6120.7		BIC	6475.4	6413.5	6374.6
	DIC	6598.8	6193.0	6062.5		DIC	6424.1	6355.8	6318.6
Oil vs bitcoin	AIC	7903.2	7739.0	7616.5	IWHCE vs bitcoin	AIC	7987.8	7788.7	7766.1
	BIC	7944.4	7784.4	7661.8		BIC	8029.0	7834.0	7811.4
	DIC	7890.8	7725.7	7605.5		DIC	7977.6	7775.9	7753.3
Natural gas vs bitcoin	AIC	7891.6	7714.5	7666.6	Bitcoin vs gold	AIC	7538.6	7385.6	7321.7
	BIC	7932.8	7759.8	7712.0		BIC	7579.8	7430.9	7367.1
	DIC	7881.5	7701.3	7652.1		DIC	7526.3	7372.1	7308.3

Table 4.5: Summary of the MCMC simulations for the model with SMGED

commodities	parameters	mean	Sd.	2.5%	25%	50%	75%	97.5%
Coal	γ	1.089	0.026	1.037	1.076	1.086	1.104	1.142
	ω	2.252	0.413	1.603	2.024	2.262	2.481	3.012
	α	0.673	0.159	0.318	0.583	0.680	0.775	0.964
	β	0.132	0.106	0.025	0.066	0.118	0.172	0.299
WTI (Oil)	γ	0.963	0.025	0.924	0.945	0.962	0.976	1.019
	ω	2.006	0.646	0.868	1.625	1.949	2.271	3.562
	α	0.150	0.025	0.108	0.132	0.152	0.163	0.201
	β	0.806	0.031	0.747	0.786	0.802	0.829	0.865
Natural Gas	γ	0.994	0.031	0.933	0.979	0.993	1.015	1.050
	ω	9.171	3.112	3.925	6.839	9.317	11.042	16.061
	α	0.221	0.032	0.155	0.204	0.222	0.241	0.280
	β	0.709	0.048	0.603	0.678	0.713	0.747	0.790
IWHCE	γ	0.938	0.038	0.879	0.917	0.942	0.959	0.999
	ω	2.716	0.725	1.353	2.324	2.700	3.075	4.206
	α	0.156	0.023	0.103	0.146	0.160	0.167	0.191
	β	0.829	0.023	0.791	0.816	0.826	0.838	0.882
Bitcoin	γ	0.968	0.024	0.928	0.955	0.967	0.981	1.017
	ω	14.763	5.164	5.481	11.406	14.420	18.355	24.611
	α	0.192	0.036	0.087	0.186	0.202	0.213	0.228
	β	0.792	0.034	0.755	0.770	0.782	0.800	0.889
Gold	γ	0.929	0.038	0.880	0.906	0.928	0.952	1.008
	ω	0.113	0.058	0.024	0.068	0.107	0.150	0.236
	α	0.119	0.024	0.075	0.099	0.119	0.138	0.164
	β	0.866	0.024	0.822	0.847	0.866	0.888	0.908
	δ	0.798	0.030	0.739	0.779	0.797	0.822	0.857
	a	0.203	0.020	0.173	0.194	0.204	0.213	0.233
	b	0.666	0.034	0.611	0.650	0.668	0.686	0.714
	$a+b$	0.869	0.054	0.785	0.845	0.872	0.899	0.947

Table 4.6: The Bayesian DCC-MGARCH(1,1) estimation results for the bivariate model with SMGED

Bivariate	parameters	mean	Sd.	2.5%	25%	50%	75%	97.5%
Coal vs IWHCE	*a*	0.046	0.039	0.001	0.016	0.037	0.067	0.151
	b	0.303	0.194	0.015	0.155	0.282	0.420	0.756
Coal vs Gold	*a*	0.028	0.026	0.001	0.009	0.020	0.039	0.094
	b	0.383	0.227	0.046	0.186	0.360	0.546	0.870
Coal vs Bitcoin	*a*	0.045	0.040	0.001	0.013	0.035	0.065	0.146
	b	0.470	0.220	0.073	0.296	0.493	0.639	0.884
WTI (Oil) vs IWHCE	*a*	0.284	0.043	0.209	0.255	0.281	0.311	0.377
	b	0.592	0.066	0.459	0.548	0.597	0.639	0.707
WTI(Oil) vs Gold	*a*	0.252	0.046	0.153	0.224	0.254	0.284	0.332
	b	0.667	0.059	0.566	0.627	0.663	0.701	0.806
WTI(Oil) vs Bitcoin	*a*	0.240	0.050	0.092	0.216	0.245	0.272	0.324
	b	0.643	0.068	0.528	0.594	0.635	0.690	0.784
Natural Gas vs IWHCE	*a*	0.321	0.082	0.216	0.273	0.302	0.345	0.520
	b	0.522	0.209	0.044	0.525	0.612	0.652	0.706
Natural Gas vs Gold	*a*	0.326	0.271	0.056	0.151	0.235	0.273	0.311
	b	0.534	0.588	0.100	0.395	0.525	0.587	0.656
Natural Gas vs Bitcoin	*a*	0.432	0.301	0.055	0.200	0.265	0.299	0.334
	b	0.376	0.590	0.078	0.399	0.544	0.602	0.646
Coal vs WTI(oil)	*a*	0.064	0.042	0.006	0.032	0.058	0.089	0.167
	b	0.378	0.172	0.084	0.247	0.377	0.492	0.744
Coal vs Natural Gas	*a*	0.038	0.031	0.002	0.015	0.029	0.054	0.116
	b	0.395	0.246	0.019	0.176	0.386	0.586	0.872
WTI(oil) vs Natural Gas	*a*	0.219	0.058	0.120	0.179	0.214	0.254	0.345
	b	0.272	0.147	0.041	0.168	0.251	0.354	0.615
Gold vs Bitcoin	*a*	0.138	0.040	0.080	0.109	0.131	0.158	0.232
	b	0.784	0.087	0.579	0.756	0.803	0.836	0.881
Gold vs IWHCE	*a*	0.201	0.043	0.119	0.176	0.200	0.227	0.283
	b	0.759	0.049	0.651	0.731	0.763	0.792	0.838
Bitcoin vs IWHCE	*a*	0.295	0.046	0.216	0.268	0.293	0.322	0.384
	b	0.595	0.059	0.462	0.564	0.599	0.634	0.702

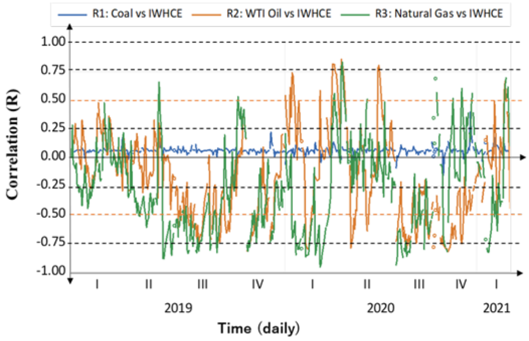
4.5.3 The time-varying conditional correlations

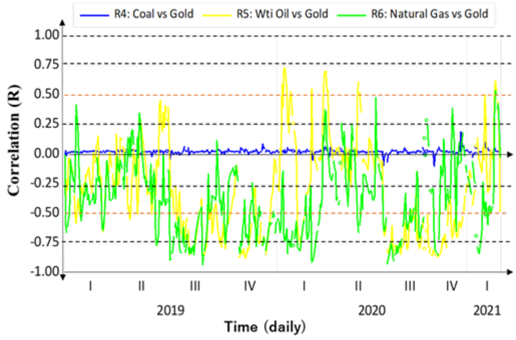
Based on the results in Table 4.4, we applied the Bayesian DCC-MGARCH model with the SMGED to estimate the time-varying conditional correlations (R_t in equantion (3)) between the fossil fuel and the financial market.

The results of the fossil fuel relation to IWHCE are shown in Figure 4.5(a). Noteworthily, during the COVID-19 period, the correlations between IWHCE and coal are almost positive value and the fluctuation range is smaller compared to that of IWHCE to WTI crude oil and Natural Gas (Figure 4.5(a): R1). The nexus between IWHCE and WTI crude oil fluctuates between positive and negative correlation values -0.8 to 0.8 before and after 2020, while it become a negative correlation from June 2020 to January 2021 (Figure 4.5(a): R2). In addition, the relationship between IWHCE and Natural Gas fluctuates between positive and negative correlations from 2020 to 2021(Figure 4.5(a): R3). The result in Figure 4.5(a) indicate that the IWHCE relation to oil and natural gas is stronger than the correlation between IWHCE and coal, and then their relationship shifts from negative to positive after 2020 because the IWHCE, oil, and natural gas in the US were all affected by COVID-19 (World resources institute, 2020).

Figure 4.5(b) shows the DCC conditional correlations between fossil fuel and gold. It is evident from Figure 4.5(b) that the correlations between coal and gold are also almost positive and that there is only a small fluctuation range before and after covid-19 periods (Figure 4.5(b): R4), while the relationship between WTI and natural gas and gold is stronger, alternating between positive (0.8) and negative values (-0.8) ((Figure 4.5(b): R5, R6)), their relationship also changes from negative to positive after the pandemic as seen in figure 4.5(a). From Figure 4.5(c), we can observe that the correlation between fossil fuels and Bitcoin fluctuates between positive and negative in the COVID-19 period, and the relationship between Bitcoin and WTI crude oil and natural gas also becomes stronger, but not as strong as the correlation between fossil fuels and IWHCE and gold. This may be because Bitcoin acts only as a diversifier for fossil fuel portfolio investments (Dutta et al., 2020).

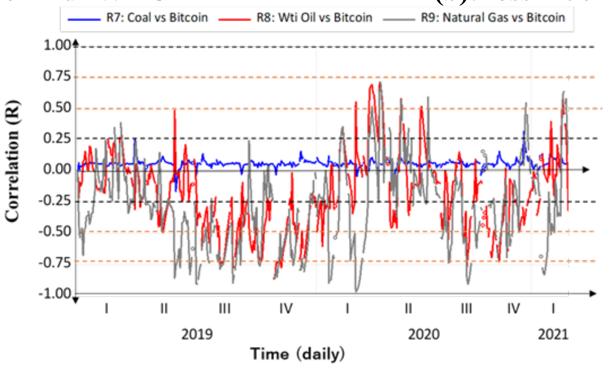
Finally, Figure 4.5(d) displays the correlation among coal, natural gas, and WTI crude oil, while Figure 4.5(e) focuses on the linkage among IWHCE, Bitcoin, and gold. Noteworthily, the magnitude of IWHCE and gold correlation displays higher positive values (Figure 4.5(d): R14) before and after the covid-19 period. There is also a small minor positive relationship between coal and WTI crude oil and natural gas, with the correlation of WTI and natural gas being stronger during the COVID-19 period (Figure 4.5(e)).



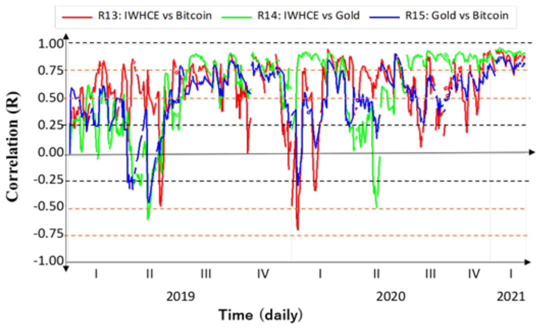


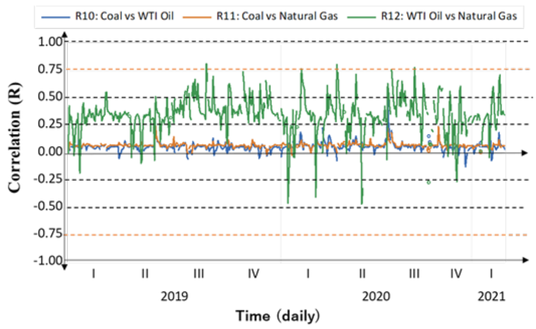
(a): fossil fuel and IWHCE

(b): fossil fuel and Gold



(c): fossil fuel and Bitcoin





(d): Among financial market

(e): Among fossil fuel

Figure 4.5: The time-varying conditional correlations between fossil fuel and clean energy

4.6 Discussion

In this study, we find a GARCH effect between fossil fuel and its hedging assets based on the LM test. This means that the volatility between them is related. Moreover, we also suggest that the Bayesian DCC-MGARCH model with the SMGED is credible for estimating the DCC conditional correlations between them. As per the results shown in Table 5, we can conclude that the values of a + b in equation (6) are less than 1 in all bivariate models, indicating the existence of the time-varying conditional correlations. This implies that the conditional correlations between our interesting fossil fuel and its hedging assets prices returns are time-varying during the pandemic period. This confirms the result of Zhang et al (2021) revealing that the linkage between energy and the stock market is dynamic in the context of Covid-19. We also confirm that nexus with their hedging assets tend to have a stronger negative correlation before the pandemic and a stronger positive correlation value after the pandemic (Figure 4.3).

A possible reason for this is as follows. In order to mitigate their risks, energy investors in oil and natural gas usually need to make a portfolio plan based on MPT. In this theory, a negative or low correlation is a key concept for creating diversified portfolios that can better withstand portfolio volatility. Gold, clean energy stocks, and Bitcoin are most likely to be selected as hedging assets to diversify investment portfolios in the energy market (Dutta et al., 2021). This might indicate that crude oil and natural gas have a stronger negative correlation with these markets before the pandemic because diversification works best when the assets are negatively correlated with one another, such that, as some parts of the portfolio fall, others rise. However, during the early days of the pandemic, crude oil and natural gas in the US suffered from negative influences related to COVID-19 (World resources institute, 2020; Mensi et al., 2020), as did the IWHCE (Zhang et al, 2021), gold, and Bitcoin markets (Dutta et al., 2021). This means that, when a pandemic occurs, investors may panic and simultaneously sell crude oil, natural gas, IWHCE, and other relatively risky assets to buy relatively low-risk or low-correlation assets such as bonds. This behavior triggered by panic will cause the market prices of these assets to decline simultaneously; thus, their volatility correlation may also become positive after the pandemic.

In particular, we also find that the relationship between WTI oil and natural gas and its hedging assets has a stronger positive correlation value after the pandemic. This implies that the effect of portfolio investment between fossil fuel and clean energy stock, gold, and Bitcoin to diversify risks through negative correlation may not be as significant during the pandemic. This result is consistent with the findings of So et al. (2021), pointing out that the hedging effect in a diversified portfolio weakened due to the high positive correlation of financial markets during the pandemic. However, this finding also contradicts Dutta et al. (2020) suggesting that gold has either negative or zero correlations with the oil indexes during the COVID-19 period.

Furthermore, we also find that the relationships among the fossil fuel and financial assets only became positive for the short-term and their relationship returned negative in mid-2020. As Waggle and Agrrawal (2015) define three to six months as an indicator for short-term investments, our result might be implying that the impact of the COVID-19 pandemic on their relationship only sustained for the short-term. This indicates that for the long term the stakeholders in the fossil fuel markets were able to cross hedge their portfolios with the financial assets.

Therefore, the changes in the relationships among the fossil fuel and financial markets due to the COVID-19 pandemic became apparent in the short run but might be not as prevalent in the long term. This result is somewhat different from Chang et al.(2020), suggesting that the dynamic relationships between the fossil fuel and clean energy stock markets were dramatically affected in both the short and long run.

4.7 Conclusion

Our study employed the Bayesian DCC-MGARCH model to examines how the correlation between the fossil fuel and clean energy stock, gold, and bitcoin market is changing since the COVID-19 pandemic took place. The study identifies that the Bayesian DCC-MGARCH model with the skew multivariate generalized error distribution is credible for fossil fuel, clean energy stock, gold, bitcoin market to estimate the time-varying conditional correlations between them. Our results suggest that the fossil fuel relation to clean energy stock, gold, and bitcoin market are changing, and they have almost become positively correlated since the pandemic occurred. It is important for fostering energy and financial market stability and choosing optimal hedging strategies that minimize the diversification of risk under the situation of the pandemic. Thus, the study can offer a valuable reference for policymakers and energy traders to help their decision-making in the future.

Moreover, our results show that during the COVID-19 pandemic, the relationship between the fossil fuel (WTI oil and natural gas) and financial (IWHCE, gold, and Bitcoin) assets changed from a negative correlation to a stronger positive correlation in the short term; three to six month. However, such a positive correlation did not last for more than six months and the correlation returned negative within less than six months. This positive correlation between fossil fuels and the financial market indicates difficulties for cross-market investors to hedge across these markets in the short term. Therefore, investors should be cautious in hedging the risk across the fossil fuel and financial markets for the short term when the shock from the pandemic is evident. However, our result suggests that hedging across the fossil and financial markets is still effective for the long term when the shock of the pandemic on markets is weakening.

Our findings have some significant implications for investors and energy policymakers that are cross-hedging among the fossil fuel and financial markets.

First, as the COVID-19 pandemic did change the correlations among fossil fuel and financial markets to become negative in the short term, the stakeholders to secure fossil fuel energy should note that hedging across the fossil fuel and financial markets becomes difficult in the short term. Hence, the study provides evidence that a shock like the COVID-19 makes it difficult for the market participants to hedge the price risk involved in the fossil fuel market in the short term.

Second, given that the correlations among fossil fuel and financial markets returned negative within less than six months, the optimal hedging strategies that minimize the risk in the short and long term based on the MPT can be still effective for the long term. Thus, this indicates that hedging the price risk in fossil fuel can be still mitigated by cross-hedging with financial assets like renewable energy stock, gold, and Bitcoin in the long term. This implies that keeping track of the relationships among the fossil fuel and financial markets in the long term is important for stakeholders in the fossil fuel market to conduct a sustainable energy supply.

One limitation of this study is that the fossil fuel relation to IWHCE, gold, and Bitcoin markets is considered only during the pandemic. In future research, we should focus on the volatility spillovers between all energy and financial markets to identify which market is the transmitter/receiver of volatility to manage risk in cross-market investment during this pandemic.

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Dissertation Conclusion

The first part of the dissertation provided an overview of the empirical methodology of the TVP-VAR model with stochastic volatility, as well as its application to the pass-through rate of the JPY and CNY on the Chinese LNG import price. Moreover, part 1 suggests the importance of applying the TVP-VAR model instead of using the conventional VAR model when the parameters in the VAR model are time-variant. Part 1 also suggests the importance of considering the CNY fluctuation range when discovering or forecasting the price of the Chinese LNG import price. This implies that the LNG import price will be more stabilized when the CNY is controlled by the Chinese government. Hence, part 1 indicates the significance of considering the effects of the exchange rate on an energy market when it is likely to be influenced by a monetary reform of the importing country.

The second part of the dissertation applied the recursive cointegration test to analyze the relationship between the Chinese coal and international fossil fuel markets. I found that the long-run relationship between the Chinese coal and international fossil fuel markets was changing during the study period, implying that importing companies in China must consider the impact of the dynamic relationship between international energy prices and domestic coal prices to identify coal prices movements when purchasing coal. I also found that the Chinese domestic coal and international natural gas markets became cointegrated after 2018, signifying that after 2018, policymakers must consider the impact of international natural gas prices when formulating a policy to stabilize the Chinese coal price. These results provide important information for the Chinese government to substitute coal with natural gas to address the climate change issue until it can totally replace its fossil fuels with renewable sources.

In the third part of the dissertation, the recursive cointegration test is employed to identify whether the dynamic relationship between the Chinese and international fossil markets changed during the 2008 financial crisis and is changing during the COVID-19 pandemic. Besides, the impact of the crises is analyzed by including the periods affected by the crises as dummy variables in the VAR and VECM models. As we found that the shocks from the 2008 financial crisis and the COVID-19 on the relationships between the Chinese and international energy markets were driven by the effects on the Chinese fossil fuel market, the stakeholders in the Chinese fossil fuel market need to pay more attention to the Chinese fossil fuel market when considering the risk involved in trading between the Chinese and international energy markets. This implies that policymakers should account not only for the dynamics relationships but also attach importance to the dynamic relationship driven by the Chinese fossil fuel market when stabilizing energy prices during the crises.

In the last part of the dissertation, I verified that the Bayesian DCC-MGARCH model with the SMGED is credible to estimate the DCC conditional correlations between the fossil fuel and its hedging assets. It implied that the conditional correlations between our interesting fossil fuel and its hedging assets prices returns are time-varying during the pandemic period. Furthermore, the study revealed that the WTI crude oil and natural gas relations to IWHCE, gold, and bitcoin market are changing before and after the pandemic suggesting the importance for the policymakers to pay more attention to the change in the relationship between fossil fuel and the financial market after the pandemic.

I can conclude from this dissertation that the TVP-VAR, recursive cointegration test and Bayesian DCC-MGARCH time series model are suitable for the analyzing the energy and financial markets that are often affected by events like to the 2008 financial crisis and the COVID-19 pandemic. Especially, I found that the linkage between the energy market and financial market is more likely to change when shifts in energy and monetary policies and crises occurs. Thus, this paper provides an important reference for investors and policymakers in the energy and financial markets to conduct risk management and to give policy recommendations for stabilizing these markets.

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