Empirical Analysis on Dynamics of Commodity Prices Related to Energy Resources

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（エネルギー資源に関連するコモディティー価格のダイナミクスに関する実証分析）

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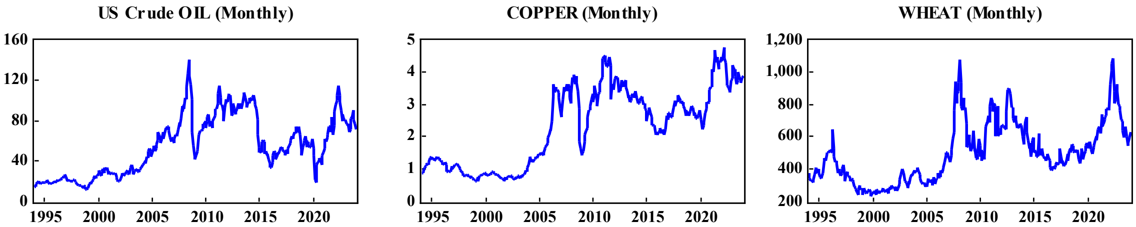
Introduction

The commodity market, once a market for trading real commodities, has over time transformed into a market with a financial function to avert risk with the stock market. As described in studies by Bodie and Rosansky (1980) and others, the commodity market came to be used for optimal portfolio selection by taking advantage of its correlation with the stock market. This trend has been particularly pronounced since the 2000s, and not only crude oil, but also various commodities such as copper and agricultural products have shown rapid growth, and some prices and market structures have changed dramatically. Figure (i) shows that the fluctuations of commodity prices has increased since 2000, and that prices have been rising steadily. In recent years, Goldstein and Yang (2022) and others have pointed out that a phenomenon known as financialization is occurring in some commodity markets, particularly the crude oil market.

Figure (i). Price trends in major commodity markets



However, as noted in the study by Pindyck (2001), the essential aspects have not changed, and commodities, which are real assets, have not lost the mechanism by which their prices are determined by supply-demand relationships and seasonality. Therefore, once a global economic stagnation such as COVID-19 occurred, the demand for crude oil decreased significantly as production activities themselves ceased. But there is a limit to how much can be stored, so the mismatch between supply and demand resulted in a negative price for West Texas Intermediate (WTI) crude oil futures, the U.S. crude oil futures contract, in April 2020. In response to the shock of the decline in the crude oil market, fear index also recorded abnormally high values. Many investors were reminded by the fear index that this was still an unusual situation. Nevertheless, there is little argument as to the correctness of this intuition.

For example, OVX, the crude oil version of the fear index, is believed to be negatively correlated with the crude oil market, but there are few cases where this is really true or has been pursued in depth. From a theoretical background, implied volatilities such as OVX are said to have both positive and negative correlations with stock returns. If the correlation is positive, the phenomenon is defined as the volatility feedback effect (French et al., 1987), and if the correlation is negative, the phenomenon is defined as the leverage effect (Black, 1976). Therefore, it is not surprising that either a positive or negative correlation can occur, but in order for it to be a valid fear index, it must be negative. The question then arises as to whether the negative correlation between the OVX and the crude oil market is consistent even when reflecting the internal and social conditions of the market. This perspective is still in its infancy in the empirical analysis of commodity markets, and can be considered the starting point for the unique approach that this paper takes.

Second, this paper also focuses on the relationship between the oil market and the real economy. With the progression of Ukraine by Russia in 2022, Europe, constrained by gas supply, was forced to review its own energy policy due to soaring gas prices, and the weakening of the de-resource fuel banner is also highly impressive. As shown above, our intuition is that commodity markets are affected not only by supply and demand, but also by geopolitical factors and trends in the real economy. The most obvious example is the relationship between the situation in the Middle East and oil shocks. Therefore, the second research project is to examine the relationship between the price dynamics of the oil market and the mechanism of the shipping index, which is closely related to the real economy, from a long-term analytical approach, and to examine what triggers changes in this relationship.

On the other hand, research is also occurring on energy-related mineral markets. In the context of the energy transitions that are taking place around the world, such as decarbonization and the expansion of electrification, research on the relevant minerals, commonly referred to as critical minerals, has not yet been developed from a financial approach. Most studies are broadly categorized and correlated with, for example, metals groups and stock markets. While some research has been conducted on minerals such as gold and platinum, which are important as asset values, nickel and copper are largely unexplored. Similarly, considering the future outlook for social structure and the importance of securing important minerals for the expansion of renewable energy, it is worthwhile to examine whether there is investment value at this point and what the structure of profitability is like. For this reason, it was chosen as the final subject of this paper's research. Based on these perspectives, this paper will provide an empirical analysis focusing on the relationship between the crude oil market and fear indices, trends in the real economy and the crude oil market, and the returns of key mineral markets related to the energy sector.

As a last of the introduction, it will be provided an overview of the research and empirical results in each chapter. Chapter 1 is an attempt to examine regime switches in the empirical relationship between return dynamics and implied volatility in energy markets. The time-varying characteristics of the return generation process are defined as a function of several risk factors, including oil market volatility, stock price and exchange rate fluctuations. The empirical results are based on a Markov regime switching model, particularly its ability to capture the stochastic behavior of the oil version of the fear index (OVX) as a benchmark for investors' fears. The results suggest that the dynamics of oil market returns are governed by two distinct regimes: a state driven by a negative relationship between returns and implied volatility, and another state characterized by a more pronounced negative correlation. 2008 to 2021 sample period, the former regime with weak negative correlations dominates, but the frequency of regime shifts also appears to increase under more volatile oil price dynamics associated with important events such as the COVID-19 pandemic. Thus, evidence of a negative correlation structure turns out to be robust to changes in the estimation period, suggesting that OVX, the crude oil version of the fear index, remains a reliable indicator of market sentiment in the energy market. Chapter 2 attempts to verify the determinants factors of fluctuations in the dynamic correlation between the U.S. crude oil market and the global shipping index. Dynamic correlations are estimated from monthly data on the U.S. crude oil futures market and the Baltic Dry Index from 1997 to 2023 using the diagonal-BEKK model, followed by an empirical analysis of the correlations with each of the three groups of markets (risk, financial markets, and economic trends). The empirical results provide that the estimated dynamic correlations have tendency to be correlated with risks such as policy-related uncertainty, market returns on U.S. stock market and changes in producer prices. And this mechanism is evidence suggesting factors that complicate the fluctuations in the dynamic conditional correlations between the oil returns and maritime returns. In Chapter 3, the empirical analysis focuses on the profitability of the mineral market, which is needed for economic and production activities, referred to as critical minerals. In particular, it aims to determine whether the WilderHill New Energy Global Innovation Index (WH NEX), defined as sentiment reflecting rising investment in renewable energy, is a determinant of higher profitability in the nickel, cobalt, and copper markets. It also examines whether the monthly profitability of financial markets and business cycle fluctuations are determinants. The study will use monthly data from 2006 to 2023 to conduct multiple regression analysis and a state-space model. The empirical results indicate that WH NEX is a determinant of higher monthly profitability in the nickel and copper markets. On the other hand, the only determinant that increases monthly profitability in the cobalt market is business cycle fluctuations. From the estimation of the state equation using the state space model, it was observed that the correlation coefficients also changed significantly during periods of large changes in the prices of the markets that were the determinants or the explained variable, respectively. The Last chapter, conclusion reviews and summarizes the contents of the chapters, followed by a summary of the economic and policy implications obtained through the empirical analysis and future research issues, including the limitations of the study that emerged from each of the empirical analyses.

Chapter 1. Markov-Regime Switches in Oil Markets: The Fear Factor Dynamics

1. Introduction

The dynamics of energy markets have strong bearing, not only on various aspects of social life, but also on economic activities, monetary policies, and investment decisions. Price signals from the crude oil market, in particular, have significant effects on the behavior of inflation expectations, and in turn, institutional investors and policy-makers. It may be also argued that the price dynamics are reflective of the aggregate impact of megatrends, including demographic and social changes, technological innovation, natural resources, financial globalization, rapid urbanization, and shift in eco-nomic power, inter alia. It is not clear how this complex web of underlying forces may affect the energy markets, and for instance, their essential linkage with the equity and currency markets. The existence of latent variables has the potential of creating non-linear relationships that may not be easily reflected by linear regression models. Thus, shifts in the relationship between price variations in energy markets and equity returns as well as currency changes between different states of the latent variables may be better captured by Markov-regime switching models. It is the principal objective of the present study to examine the inter-market linkages as well the inner dynamics of the risk-return tradeoff relationship in oil futures markets.

Conventional wisdom suggests that market perceptions of increased economic uncertainty are likely to be accompanied with lower asset valuation and expectations of higher volatility and increasing volatility. The negative relation between returns and changes in volatility expectations in equity markets is usually assessed using model-free volatility benchmarks such as the Chicago Board Options Exchange's VIX index, which is regarded as a gauge of investors' fear. The fear factor dynamics, measured by changes in OVX volatility index, may constitute a significant determinant of shifts in the risk-return tradeoff in oil futures markets. The OVX volatility index is derived from the option prices of Exchange Traded Funds that are linked to spot WTI prices, and provides a forward-looking measure of market volatility in terms of future oil price fluctuations. The focus on the risk-return dynamics of WTI markets is justified by the crucial role that energy markets play in the real economy and their intrinsic relation-ship with financial markets. Indeed, unlike financial markets, commodity markets including crude oil futures, have a tendency to exhibit price seasonality, reflecting shifting risks associated with oil production and consumption due to changes in supply and demand functions, in addition to geopolitical risks.

Thus, a better understanding of the dynamics of oil futures returns may shed light on the significance of market sentiment and investors' fear, on the linkage between the real economy and financial economy, and particularly on the impact of the com-pounded healthcare and economic crises. Indeed, the Covid-19 pandemic was characterized by expectations of heightened economic uncertainty, sharp falls in WTI futures, with negative pricing reflecting the effects of economic lockdowns in terms of the underutilization of production factors and disruptions to supply chains. The econometric approach is based on Markov-regime switching models, which have the capacity of capturing abrupt changes in the correlation structure and the propensity of oil markets as well as financial markets to behave differently during periods of lower and higher economic uncertainty. Thus, Markov-regime switching models can be useful, indeed, in better understanding the shifting behavior of energy markets and anticipating changes in the correlation structure in response to significant events.

To the best of the author's knowledge, this paper provides new evidence about the prevalence of a Markov-regime of weaker negative correlation under more volatile markets. The empirical results suggest that futures returns are governed by two latent states exhibiting significant negative correlations between WTI futures returns and OVX daily changes. The new evidence indicates that regime shifts are more likely to occur in association with market expectations of increasing volatility and diminishing oil returns. Futures returns during periods of increased uncertainty tend to be governed by abrupt switches between regimes of weaker and stronger negative correlations with OVX, reflecting changing levels of investors' fear. In addition, the new evidence suggests that economic lockdowns in response to disease outbreak have the potential of increasing the likelihood of Markov regimes with more pronounced negative correlation between oil futures returns and changes in volatility expectations. In contrast, periods of financial instability, such as the U.S. credit crisis, have the potential to weaken or impair the inherent relationship of oil futures returns with volatility expectations, and instead strengthen the linkages with currency fluctuations and equity valuation.

The remainder of the paper is organized as follows. Section 2 provides a brief re-view of literature related to the VIX model-free volatility index and the empirical evidence about its correlation equity returns. Another strand of literature is related to the OVX volatility-return inner dynamics of WTI futures market as well as its correlation with other asset markets. Section 3 describes the Markov-Regime Switching model-ling of WTI return dynamics. Section 4 presents the sample data including WTI futures, oil volatility index, S&P 500 stock price index, and U.S. dollar index. It describes the distributional properties, and discusses the estimation results of Markov-regime switching models for the full sample period. The empirical evidence is also inclusive of robustness tests required to examine the stability of the correlation structure over time. The final section concludes the paper.

2. Literature Review

The model-free methodology underlying the calculation of the VIX volatility index by the Chicago Board Options Exchange (CBOE) is shared by many other volatility in-dices, including the OVX index for crude oil futures markets. The volatility index pro-vides a forward-looking measure of market sentiment in terms of expectations about future levels of price volatility. The VIX index reflects the volatility implicit in a hypo-thetical option on the S&P 500 index assuming a constant time to expiration of thirty days. This volatility index is widely regarded also as a measure of investors' fear because of its negative correlation with returns. There is a strong tendency for the anticipated level of volatility to increase under bearish markets and decrease under bullish markets. Theoretically, the sensitivity of volatility expectations to fluctuations in the price of the underlying asset is an intrinsic feature of option pricing. Thus, perceptions of increasing economic uncertainty by option market participations are bound to be accompanied by lower asset valuations and expectations of higher volatility in the underlying asset market. This proposition about the return-volatility dynamics is expected to apply with equal force in options and underlying markets, independent of the nature of assets, including equities and commodities.

Earlier studies by Fleming et al. (1995), and Connolly et al. (2005), among others, provided evidence of strong negative correlation between the VIX index and stock market returns[1]. Sarwar (2012) presented further evidence on this empirical relation-ship based on contemporaneous variables, and suggested that a decline in equity prices is conducive to market perceptions of increased uncertainty, and in turn, higher volatility expectations. The original work by Whaley (2000, and 2009), and more recent studies by Smales (2022), among others, indicate that the VIX functions as a fear index for market investors. The development of comparable volatility indices for other markets, such as the VXJ index from the Nikkei 225 option prices by Nishina, Maghrebi, and Kim (2006) for the Japanese markets, and from the Kospi 200 options for the Korean markets by Maghrebi, Kim, and Nishina (2007) provided additional evidence about the usefulness of the model-free implied volatility index a gauge of investors' fear and market sentiment. An alternative version of model-free volatility is proposed by Fukasawa et al. (2011) based on the approximation of the expected quadratic variations of asset prices in relation to options prices[2].

Part of the empirical literature focuses also on the stochastic behavior of volatility indices in relation with asset bubbles, financial crises, and macroeconomic shocks. For instance, some empirical evidence is provided by Szado (2009), Nishina et al. (2012), Maghrebi et al. (2014) and Baiardi et al. (2020), among others, with respect to credit crises and financial instability. Earlier evidence from Giot (2003) and Maghrebi et al. (2007) sheds light on regime switches in relation to the Asian currency crisis. More re-cent studies by Just and Echaust (2020) and Grima et al. (2021) provide evidence about the behavior of volatility expectations in association with the Covid-19 disease out-break. Thus, many empirical studies of the nonlinear dynamics of volatility expectations in equity options markets are based on Hamilton's modelling of Markov-regime switches.

Another strand of literature focuses on the relevance of commodity markets, including crude oil, in explaining the behavior of returns in equity, bond, and foreign exchange markets[3]. Part of the reason for the focus of empirical analysis on energy markets lies in the need to examine the effectiveness of including commodity markets for portfolio risk diversification purposes. In this context, the study by Beckmann et al. (2020) examines the relationship between WTI futures and exchange rates, which reflects the extent of international trade. Given their importance for the real economy, and relationship with financial markets, crude oil markets are the subject of a growing literature aimed at better understanding the price and volatility dynamics. The OVX

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[1] It is noted that the study by Fleming et al. (1995) was performed with a volatility index based on the S&P 100 stock market index, formerly known as VIX index.

[2] The focus is also placed, as in Mencia and Sentana (2013), on the valuation of VIX derivatives, where the volatility index serves as the underlying asset for derivatives contracts.

[3] See for instance, Kim et al. (2019), Wang and Xie (2012), Choi and Hammoudeh (2010), Mensi et al. (2013), Raza et al. (2016) and Creti et al. (2013), inter alia.

volatility benchmark is an index calculated based on the CBOE's VIX methodology, but it is rather derived from the option prices of Exchange Traded Funds (ETFs) that are intrinsically linked to WTI option prices. Thus, in a sense, the OVX index is an aggregation of volatility expectations by participants in the ETFs rather than crude oil markets.

Crude oil markets are intrinsically different from equity markets. Commodity prices exhibit seasonality and are strongly sensitive to economic activities, with risks associated with the production and consumption functions. Crude oil is traded as a re-al asset and market prices are sensitive to a delicate balance between supply and demand, which is influenced by geopolitical risks, among others. The literature is inclusive of many studies, including Pindyck (2001), Hamilton (2008), and Gong and Xu (2022), among others, that consider the dynamics and determinants of commodity markets as well as the impact of geopolitical risk. It is also noted that market participants tend to trade crude oil not just to facilitate economic activities but for speculative purposes as well. Thus, it is important to understand the nature of crude oil markets and their stochastic behavior under different levels of economic uncertainty.

There is a rich literature on the nature of commodity exchanges and their relationship with financial markets. The empirical evidence from Dupoyet and Shank (2018) suggests that changes in the OVX index are positively related to stock market returns in the manufacturing, energy, and utilities sectors, and negatively related to those in durable consumer goods and wholesale trade sectors. Earlier evidence from Bodie and Rosansky (1980) suggests that it is possible to make recourse to alternative investments to hedge risk in financial markets by focusing on the nature of commodities. More recent studies by Tang and Xiong (2012), Silvennoinen and Thorp (2013), and Cheng and Xiong (2014) provide evidence about a process of financialization of commodity markets reflecting the prevailing structures of stock markets. The impact of financialization on commodity markets is shown, by Goldstein and Yang (2022) to be linked with the real economy. It is important to understand also the impact of energy price fluctuations on the real economy and the behavior of financial markets and institutions. As noted in Dutta (2017), the observed levels of oil market volatility are significantly higher than price fluctuations in stock markets. Also, the Federal Reserve Board (2022) argues that the volatility in commodity markets, including energy re-sources and food, may pose significant risks to the stability of the financial system. A heightened systemic risk is reflective of the sensitivity of the real economy to unexpected variations in energy and commodity markets.

Other earlier studies by Bodie and Rosansky (1980), Cheung and Miu (2010), and Jensen et al. (2000), among others, examined the effectiveness of risk diversification based on commodities markets. Also, Gorton and Rouwenhorst (2006) provide evidence that the returns on commodity futures tend to be negatively correlated with stock market returns and bond returns, and that commodity futures are positive correlated with inflation as well as unanticipated inflation and changes in expected inflation. Given these stylized facts about commodity futures, further research has shed more light on the correlation structure between commodities and other asset markets and over different time periods. For instance, Lombardi and Ravazzolo (2013) develop a Bayesian Dynamic Conditional Correlation model that can account for time-varying correlation patterns between commodity and equity returns, and show that it is possible to obtain more accurate density forecasts. Furthermore, Baumeister and Kilian (2012, and 2015) on oil price forecasting. There is also a growing literature using Ma-chine Learning and deep learning in an attempt to obtain more accurate forecasts. The crucial importance of crude oil markets and their linkages with alternative markets is manifest in several empirical studies, including the work by Ferraro et al. (2015) who examine the potential of predicting exchange rates from crude oil prices.

Accordingly, there is growing literature on the return dynamics of WTI futures and their relationship with volatility expectations and other risk factors including fluctuations in stock prices and exchange rates. For instance, Aboura and Chevallier (2013) found a positive correlation, or inverse leverage effects, between changes in OVX levels and oil prices in association with the onset of the U.S. credit crisis. The evidence suggests that the positive relationship may be reflective of consumers' fear of higher oil prices, which stands in sharp contrast with the nature of fear in equity markets about downside price movements. The empirical study by Chen et al. (2015) suggests, however, that WTI futures returns and OVX daily changes are negatively correlated over a sample period partly overlapping with that of the study by Aboura and Chevallier (2013). Further empirical studies by Liu et al. (2017) and Dupoyet and Shank (2018) present similar evidence of negative correlation or asymmetric dependence based on mixed copula and GJR-GARCH models, respectively. The latter study suggests also that volatility expectations measured by the OVX index have a greater influence on financial markets than oil prices themselves, and that both oil volatility and prices are significantly related to corporate bond credit spreads.

Thus, given the mixed evidence on the dynamics of risk-return tradeoff, and the growing literature on the proposition that oil volatility expectations are also contingent on returns in foreign exchange and financial markets, it is important to explore the nonlinear dynamics of the WTI futures returns and OVX index over more recent periods, including the long-term effects of financial crises and disease outbreaks. The present study uses Markov-regime switching models, which have the capacity of capturing abrupt changes in the correlation structure and the propensity of oil markets as well as financial markets to behave differently during periods of lower and higher economic uncertainty. Of particular interest is the market behavior during the Covid-19 pandemic with heightened volatility expectations and negative pricing of WTI futures, which are reflective of the effects of economic lockdowns in terms of the underutilization of production factors and disruptions to supply chains. Modelling the return dynamics of oil futures with Markov-regime switching models can be useful in better understanding the stochastic behavior of energy markets, which are different in nature from financial markets, but may exhibit similar regime shifts in response to significant events.

3. Markov-Regime Switching Modelling of Return Dynamics in Oil Futures Markets

The empirical analysis of the return dynamics of crude oil futures is based on the Markov-regime switching model proposed by Hamilton (1989). Futures returns $y_{WTI,t}$ can be simply expressed with a first-order autoregression

$$y_{WTI,t} = \omega_{s_t} + \alpha_{s_t} y_{WTI,t-1} + \varepsilon_t \qquad [1]$$

where the disturbance terms are white noise distributed with $\varepsilon_t \sim i.i.d.N(0,\sigma^2)$. The drift term ω_{s_t} and auto-regressive coefficient α_{s_t} are assumed to depend on the state s_t prevailing at time t. This allows for the intercept value, for instance, to change from ω_1 to ω_2 with an imperfectly predictable change in the average level of the return series $y_{WTI,t}$ from one state to another at time t. Similarly, the auto-regressive term α_{s_t}, which reflects the degree of mean reversion or long memory, is allowed to adapt to changes in the stochastic structure of the return series.

Following the empirical study by Sarwar (2012) focusing on the dynamics of the S&P500 returns as a function of contemporaneous changes in the VIX index, respectively, it is possible to express the stochastic properties of oil futures returns $y_{WTI,t}$ in equation [1] as a function of changes in the OVX index $y_{OVX,t}$ as well. Also, given the empirical evidence based on Markov-regimes switching models estimated by Baiardi et al. (2020) that S&P500 returns are likely to be negatively related to oil futures returns, it is important to account for the linkage between oil futures and equity prices. Finally, there is a need to examine also the impact of exchange rate fluctuations given the fact that WTI futures are denominated in U.S. dollars and in light of evidence from Beckmann et al. (2020) that oil futures are sensitive to currency fluctuations.

Thus, it is possible to describe the dynamics of oil futures returns $y_{WTI,t}$ as a function of the inner autoregressive terms, changes in the OVX index as a measure of investors' fear in oil markets $y_{OVX,t}$, as well as returns in currency and equity markets, expressed by U.S. dollar index returns $y_{USD,t}$, and S&P500 returns $y_{SPX,t}$, according to the following empirical model.

$$y_{WTI,t} = \omega_{s_t} + \alpha_{s_t} y_{WTI,t-1} + \beta_{s_t} y_{OVX,t} + \gamma_{s_t} y_{USD,t} + \delta_{s_t} y_{SPX,t} + \varepsilon_t \qquad [2]$$

This model equation [2] implies that at a given moment, the behavior of returns does not correlate solely with its value a moment before, $y_{WTI,t-1}$, but also with contemporaneous changes in the OVX volatility index $y_{OVX,t}$, as well as returns on the US dollar index $y_{USD,t}$, and S&P500 index $y_{SPX,t}$. As with the drift and auto-regressive parameters in equation [1], the regression coefficients β_{s_t}, γ_{s_t}, and $\delta_{s_t}$are assumed to depend on the state s_t prevailing at time t. As expressed in equation [3], the regimes are assumed to follow a first-order Markov chain in which the current state s_t depends solely on the state s_t prevailing one period before.

$$Pr\left(s_t = j \middle| s_{t-1} = i, s_{t-2} = k, \cdots, y_{WTI,t-1}, y_{WTI,t-2}, \cdots\right) = Pr(s_t = j | s_{t-1} = i) = p_{ij} \qquad [3]$$

The state s_t governing the return dynamics is a random variable that is not observed directly, but can be inferred from the observed behavior of returns. Equation [3] assumes that the probability of regime prevalence or regime shift p_{ij} depends on past observations only through the most recent state s_{t-1}. It is possible to examine the Markov-regime switches with n-states ($n \geqq 2$) for the sake of easier exposition. Model equation [2] is available to estimate for a number of unobserved states ranging from, $n = 2, \ldots, 5$ full sample period as well as the three subperiods

A, B and C. It is noted that assuming that there is two-state in the inner dynamics of WTI returns reflected markets uncertainty, which associated with a regime of lower volatility and a regime of higher volatility, empirical modelling set up a two-state Markov chain because of examining whether there is a difference in the correlation between WTI and OVX in each regime based on an economic perspective in this paper. The matrix form of the two-state Markov chain can be expressed according to equation [4], where all elements are non-negative and the sums of elements in each row are equal to unity.

$$\Pi = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \quad [4]$$

With reference to Equation [2], the parameters required in describing the regime probability are represented by the state-dependent drift ω_{s_t}, auto-regressive coefficient α_{s_t} and regression coefficients associated with the explanatory variables for the volatility index β_{s_t}, equity returns γ_{s_t}, and dollar index returns δ_{s_t}. The regime probability depends also on the variance σ^2 of the Gaussian distributed error terms ε_t, and on the transition probabilities p_{11} and p_{22}. Thus, the probability of switch from regime $s = i$ at time $t-1$ to $s = j$ at time t can be expressed as $p_{ij} = 1 - p_{ii}$. A permanent shift from one regime to another would be reflected by a transition probability of unity, but given the imperfect predictability of regime-switching events, it is more plausible that $p_{22} < 1$.

Assuming that past observations of the return series are available at time t in the set of information $\Omega_t = \{y_t, y_{t-1}, \cdots, y_1, y_0\}$, and given the vector of regression parameters $\vartheta = (\omega_s, \alpha_s, \sigma, p_{11}, p_{22})'$, it is possible to infer, at time t, the conditional probabilities $\psi_{j,t}$ for $j = 1, 2$, according to equation [5].

$$\psi_{j,t} = Pr(s_t = j | \Omega_t; \vartheta) \quad [5]$$

The inferred probabilities can be estimated, following Hamilton (1989, 1994), as the by-product of an iterative process, similar to a Kalman filter algorithm which predicts future states based on input from past estimators using $\psi_{i,t-1} = Pr(s_{t-1} = i | \Omega_{t-1}; \vartheta)$ for $i = 1, 2$. The iterative process is based on the density functions ϕ_{j_t}, which can be expressed for the two-state Markov chain according to the following Equation [6].

$$\phi_{jt} = f(y_{WTI,t} | s_t = j; \Omega_{t-1}; \vartheta) = \frac{1}{\sigma\sqrt{2\pi}} exp\left\{-\frac{(y_{WTI,t} - \hat{y}_{WTI,t})^2}{2\sigma^2}\right\} \quad [6]$$

where $\hat{y}_{WTI,t} = \omega_{s_t} + \alpha_{s_t} y_{WTI,t-1} + \beta_{s_t} y_{OVX,t} + \gamma_{s_t} y_{USD,t} + \delta_{s_t} y_{SPX,t}$ and the quadratic terms $(y_{WTI,t} - \hat{y}_{WTI,t})^2$ represent the squared errors ε_t^2. Equation [7] expresses the conditional density function of return observation y_{WTI} at time t, which can be estimated from the joint density of returns and state variable

$$f\left(y_{WTI,t}\middle|\Omega_{t-1};\vartheta\right)=\sum_i\sum_j p_{ij}\psi_{i,t-1}\phi_{j_t} \qquad [7]$$

Following Hamilton (1989), the unknown vector of the regression model parameters $\hat{\vartheta}$ can be obtained using the maximum likelihood estimates of the transition probabilities according to equation [8]

$$\hat{p}_{ij}=\frac{\sum_{t=2} Pr\left(s_t=j,s_{t-1}=i\middle|\Omega_T;\hat{\vartheta}\right)}{\sum_{t=2} Pr\left(s_{t-1}=i\middle|\Omega_T;\hat{\vartheta}\right)} \qquad [8]$$

Given the starting values of the vector of parameters $\hat{\vartheta}_0$, the iterative process generates new sets of coefficients for the drift, autoregressive terms, and explanatory variables, as well as a new estimates of the residual variance and transition probabilities. Under the assumption that the Markov chain is ergodic, it is possible to use the unconditional probabilities of Equation [5] expressed as $\psi_{i,0}=Pr(s_0=i)=\left(1-p_{jj}\right)/\left(2-p_{ii}-p_{jj}\right)$. The maximization of the sample conditional log likelihood, expressed in Equation [9] by numerical optimization, with iterative computations resulting in convergence toward the Maximum Likelihood (ML) estimates.

$$log\,f\left(y_{WTI,1},y_{WTI,2},\cdots,y_{WTI,T}\middle|y_{WTI,0};\vartheta\right)=\sum_{t=1}^{T}log\,f\left(y_{WTI,t}\middle|\Omega_{t-1};\vartheta\right) \qquad [9]$$

It is finally noted that there is a growing literature that addresses several issues in the ML estimation of Markov-regime switching models. For instance, Diebold, Lee and Weinbach (1994), and Filardo (1994) examine regime switching models where the transition probabilities are not constant as in the Hamilton (1989) but time varying in order to allow for the underlying fundamentals and exogenous variables to be included in the mechanism of transition between states. Also, Harris (1999), proposes a Bayesian Markov Chain Monte Carlo estimation of regime-switching vector autoregressions. An endogenous Markov regime-switching model proposed by Kim et al. (2008) by relaxing the assumption that the state variable governing regime shifts is exogenous. More recent study by Pouzo et al. (2022) examines the consistency of ML estimation with covariate-dependent transition probabilities. Thus, given the extensive interest in econometric models capable of capturing abrupt changes in economic cycles and financial time-series, the estimation of a standard Markov-regime switching models for the WTI futures returns may shed some light on random breaks in the inner dynamics of WTI futures returns and non-linear relationship with volatility expectations as well as equity and currency returns.

4. Empirical Evidence

4-1. Data description and distributional properties

The empirical analysis is, as noted above, based on the daily time-series data for the WTI oil futures market, its related OVX volatility index, U.S. dollar index and the S&P 500 equity index. The sample observations obtained from the Thomson Reuters database span the time period from July 2008 to December 2021. The empirical analysis is based on the available database of time-series. The starting date of the sample period coincides with the CBOE's official release of the OVX index in 2008. It is also set December 2021 as the ending date of the sample period because of a different event, the progression of Ukraine by Russia starting in 2022. It partially covers significant periods of economic uncertainty caused by the U.S. credit crisis in 2007-09 as well as the ongoing economic and healthcare crises starting in late 2019. The focus is placed in particular on the implications of the Covid-19 healthcare crisis for the inner dynamics and correlation structure changes of the WTI futures markets, therefore the sample observations are divided into subperiod A from January 2018 to December 2019, and subperiod B from January 2020 to December 2021. The reason for using January 2020 as the point of departure is based on WHO reported that a novel coronavirus was identified in late 2019 and an emergency system was put in place to deal with a pandemic that occurred in January 2020. Also, the subperiod C from July 2008 to June 2010 in order to examine the impact of the U.S. government bailout, the Federal Reserve's Quantitative Easing announcement in response to the worsening credit crisis and historical losses in the equity market.

It appears from the upper-left side of Figure 1 that the WTI futures prices precipitously dropped at the end of 2008 in association with the U.S. financial crisis, but the successive rebounds over the entire sample period in 2009, 2016 and 2020 have failed to regain the pre-crisis levels. Of particular interest is the historical fall of futures prices into negative territory and significant negative returns on April 20, 2020, in response to perceptions of heightened economic uncertainty stemming from the disease outbreak. The historical futures prices are also associated with a significant jump in expected volatility as exhibited in the upper-right side of Figure 1. Judging from the typically lower scales of returns on the U.S. dollar index and S&P 500 index reported in the lower-left and right sides of Figure 1, respectively, it appears that the currency and financial markets are relatively less volatile than the energy markets. Both return series tend to exhibit more fluctuations in the earlier part of the sample period, and a sudden surge in association with negative pricing of crude oil futures in 2020, but there is a clear tendency for both indices to increase in more recent years.

Table 1 summarizes the distributional properties of these stochastic variables. The WTI futures returns are found to be negative in average, and more volatility than other variables. The daily changes in the OVX index tend to be positive, as volatile as the associated futures returns, and skewed to the right. In contrast, the returns on both the dollar index and S&P 500 index are found to be skewed to the left, and positive in average. All time-series are also found to exhibit excessive kurtosis, which is indicative of heavy-tailed distributions. Judging from the ADF test statistics, the time-series are all found to be rejected stationary over the total sample period.

Figure 1. The behavior of prices levels and returns in WTI futures, OVX, dollar index and equity markets

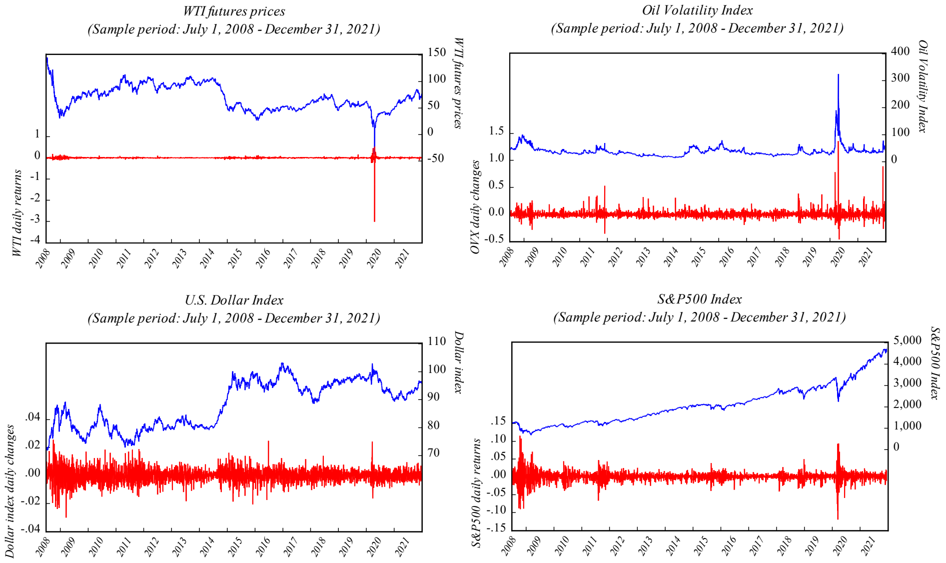


Table 1. Distributional Properties.

Distributional Moments	Mean	Std. Dev.	Skewness	Kurtosis	Jarque Bera	ADF test
WTI returns	−0.0007	0.062728	−33.5240	1569.688	3.61E+08	43.544***c
OVX daily changes	0.00174	0.063033	4.9582	87.09921	1052944.0	−61.760***a
Dollar index daily changes	0.00009	0.004761	−0.0492	5.870737	1211.493	−58.464***c
S&P500 returns	0.00045	0.012766	−0.2904	17.14844	29442.39	−68.718***a

Notes: The sample period of daily observation runs from July 1, 2008 to December 31, 2021. Significance at 1% level is denoted by asterisks *** under the MacKinnon (1996)'s one-sided probability values. The stationarity of time series is estimated with the Augmented Dickey-Fuller methodology with intercept only, with both intercept and trend terms, and with neither intercept nor trend terms are denoted by superscripts a, b, and c, respectively. Jarque-Bera statistics for normally tests are distributed as χ^2 on the null.

4-2. Model estimation results

The estimation results of equation [2] with a two-state Markov chain for the full sample period are reported in Table 2. It is noted that the estimated drift term ω_1 in Markov-regime 1 is found to be statistically insignificant. It is also associated also with an insignificant but negative autoregressive coefficient α_1, which suggests a tendency for mean reversion. The crude oil futures returns are also governed by a strong negative correlation with changes in the OVX volatility index. With significance at the one-percent level, the negative sign of the regression coefficient β_1 implies that an increase in expected volatility is associated with diminishing oil futures returns. Given the significantly negative regression coefficients γ_1 and δ_1, the dynamics of futures returns are found to be sensitive also to changes in the U.S. dollar index and equity valuation.

Table 2. Markov-regime switching model results (Full estimated period).

Model parameters	Full period (Jul. 2008 – Dec. 2021)	
	Markov-Regime 1	Markov-Regime 2
ω	−0.0001 (0.6697)	0.0174 (0.2269)
α	−0.0196 (0.1708)	0.1592*** (0.0045)
β	−0.1452*** (0.0000)	−0.9643*** (0.0000)
γ	−0.8659*** (0.0000)	−1.4004 (0.4340)
δ	0.3820*** (0.0000)	−0.6599 (0.2359)
Log(σ)	−4.1048*** (0.0000)	−1.6497*** (0.0000)
Log likelihood	9124.611	
AIC	−4.9880	
Hypothesis Tests		
$\omega_1 = \omega_2$	1.4408 (0.2300)	
$\alpha_1 = \alpha_2$	9.5865*** (0.0020)	
$\beta_1 = \beta_2$	76.7273*** (0.0000)	
$\gamma_1 = \gamma_2$	0.0259 (0.8723)	
$\delta_1 = \delta_2$	3.2807* (0.0701)	

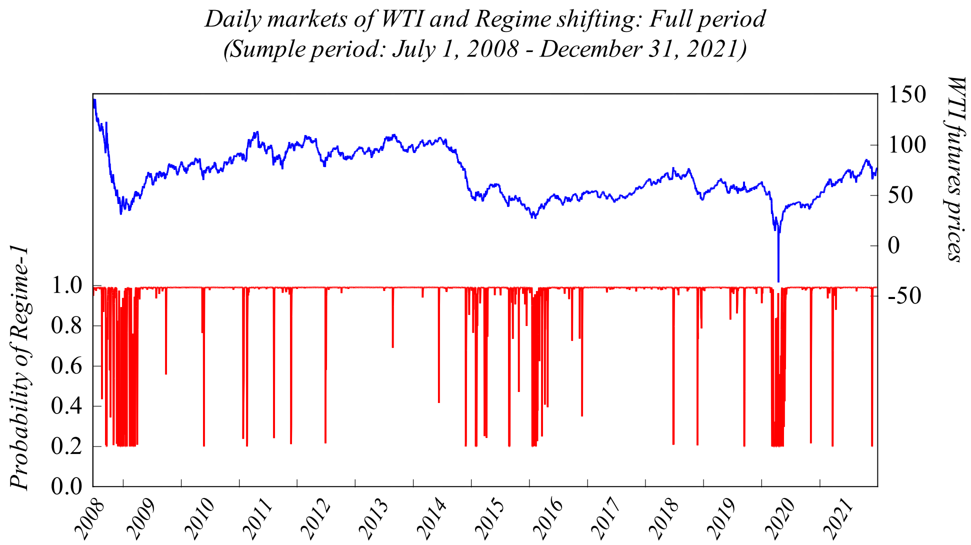
Notes: The estimated Markov-regime Switching model is represented by equation: $y_{WTI,t} = \omega_{s_t} + \alpha_{s_t} y_{WTI,t-1} + \beta_{s_t} y_{OVX,t} + \gamma_{s_t} y_{USD,t} + \delta_{s_t} y_{SPX,t} + \varepsilon_t$ .The sample period of daily observation runs from July 1, 2008 to December 31, 2021. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively. The hypothesis tests for equal coefficients are based on the Wald test following the $\chi 2$ distribution. Figures in round brackets represent probability values.

In contrast, returns governed by the Markov-regime 2 are characterized by positive but insignificant drift ω_2, positive autoregressive coefficient α_2 that implies long memory rather than mean reversion, and negative correlation with changes in volatility expectations. However, it seems that the return dynamics are not sensitive to contemporaneous variations in the U.S. dollar index or stock prices. It is noted also that both regimes are associated with significant volatility estimates, though Regime 2 seems to exhibit a relatively higher level of fluctuations. The χ^2-distributed Wald tests of hypothesis for equal regression parameters indicate that it is possible to distinguish regimes based on different autoregressive terms, as well as the structure of return correlation with changes in volatility index and equity returns. Indeed, despite the opposite signs, the null hypothesis of equal drifts cannot be rejected as both drifts are found to be insignificantly different across regimes despite the opposite signs. Whereas the oil futures returns are characterized with mean reversion in Regime 1, they tend to exhibit long memory in Regime 2. The Wald test results indicate that it is difficult to distinguish between regimes on the basis of the relationship between returns on oil futures and U.S. dollar index. However, difference between the regression coefficients associated with equity returns is found to be significant only at the ten-percent level. It is the extent to which the correlation with changes in the OVX index that seem to be most prominent in distinguishing between regimes. Thus, a transition from a regime of lower volatility to one of higher volatility, i.e., from Regime 1 to Regime 2, is accompanied with an increase in the significance of negative correlation with volatility expectations. This new evidence sheds light on the shifting expectations of market participants about future levels of uncertainty, and the need to consider the dynamics of investors' fear as a significant determinant of the return-generating process.

It is possible to examine the frequency of switches between the latent states based the probability of Regime 1, which is shown in Figure 2 together with the time-series of daily WTI futures prices. It is clear that it is Regime 1 of lower volatility that tends to dominate over long durations, but there are frequent shifts to Regime 2 at the beginning of the total sample period from August 2008 to April 2009 and in association with periods of persistent price falls from January 2016 to May 2016 as well as with the precipitous decrease in futures prices in April 2020 from March 2020 to June 2020. This evidence is partly consistent with the Chow test of structural break in the same model equation [2], which indicates the existence of a single break dates December 25th 2019, at the 5% significance level (F-Statistic 173.992, Bai-Perron critical value 18.23). This result seems to be consistent with the empirical evidence from the estimated Markov-regime switching model, which suggests frequent regime shifts in relation with the onset of the disease outbreak in December 2019, as well as the subsequent government responses and market reactions over the crisis period from March 2020 to June 2020. Thus, it seems that the dynamics of oil futures returns are responsive to the policy responses of the U.S. government to the onset of the credit crisis, as well as to the heightened levels of uncertainty about the global economy in association with the disease outbreak. Market perceptions of higher economic uncertainty in association with major events are conducive to abrupt shifts from a regime characterized by long memory rather than mean reversion and stronger rather than weaker negative correlation with the forward-looking measure of oil volatility. Indeed, the higher the perceived levels of uncertainty in the crude oil markets, the stronger the negative correlation between WTI futures returns and changes in volatility expectations.

Thus, the graphical evidence from Figure 2 suggests that regime shifts are more likely to occur frequently during periods of decreasing WTI futures prices and higher economic uncertainty. In order to examine the non-linear dynamics prior and during the disease outbreak, the model equation [2] with a two-state Markov chain is estimated for both subperiod A from January 2018 to December 2019 and subperiod B from January 2020 to December 2021. Judging from the results reported in Table 3 for subperiod A, it appears that futures returns are governed by two distinct regimes characterized by different levels of volatility. Regime 1 is associated with statistically insignificant drift and autoregressive term as well as insignificant relationship with equity returns, but with negative correlations with changes in the OVX volatility index, and in the dollar index. Thought the latter is significant only at the ten-percent level, it is found to be insignificant under the alternative regime. Indeed, futures returns are characterized, under Regime 2, by positive drift and positive correlation with equity returns, albeit significant only at the ten-percent and five-percent levels, respectively.

Figure 2. Probability of Regime – 1 (Full sample period July 2008 – December 2021)



There is also evidence that Regime 2 implies mean reversion and positive correlation with changes in the OVX index. In contrast to Regime 1 and to both regimes for the full sample period, the significance of the β_2 coefficient suggests that futures returns tend rather to rise in association with increasing uncertainty. This is consistent with the evidence from Aboura and Chevallier (2013) who found a positive correlation between changes in OVX levels and oil prices in association with the onset of the U.S. credit crisis. Judging from the tests of null hypotheses for equal regression coefficients, it appears that the Markov regimes can be distinguished not so much on the basis of differences in the correlations with currency and equity returns as differences between autoregressive terms and correlation with volatility expectations.

Table 3. Results of Subperiod A and B estimated with Markov-regime switching modelling.

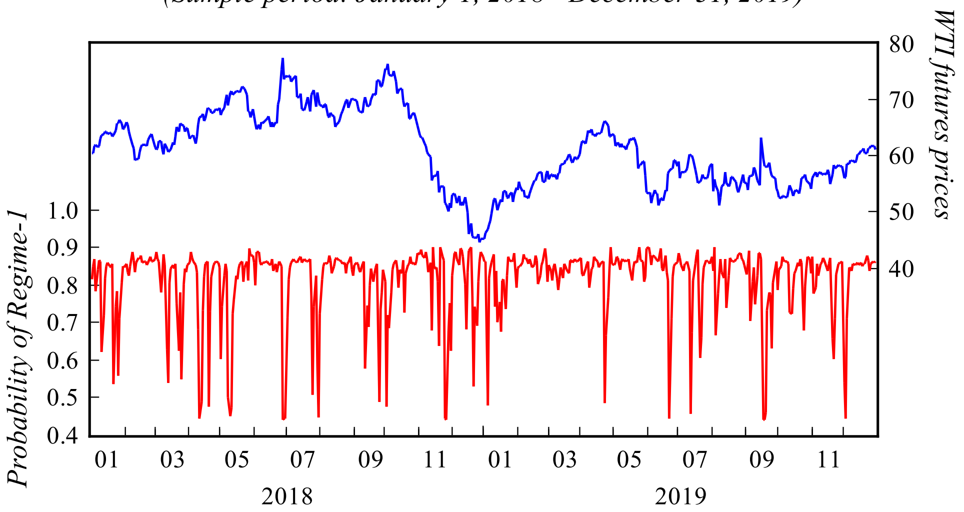
Model parameters	Subperiod A (Jan. 2018 – December. 2019)		Subperiod B (Jan. 2020 – Dec. 2021)	
	Regime-1	Regime-2	Regime-1	Regime-2
ω	−0.0009	0.0056*	0.0014*	0.0135
	(0.2648)	(0.0811)	(0.0835)	(0.7792)
α	0.0145	−2.4246**	0.0014	0.1383
	(0.7738)	(0.0153)	(0.9667)	(0.1553)
β	−0.2205***	0.2100***	−0.1802***	−1.2691***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

γ	-0.4526*	-0.1772	-0.5188**	-2.3555
	(0.0671)	(0.8440)	(0.0379)	(0.7371)
δ	0.0913	0.8216**	0.2888***	-1.9662
	(0.3084)	(0.0488)	(0.0003)	(0.1892)
$Log(\sigma)$	-4.3179***	-3.7329***	-4.1164**	-1.1437***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log Likelihood	1403.674		1219.407	
AIC	-5.324421		-4.609587	
Hypothesis tests				
$\omega_1 = \omega_2$	3.4875*		0.0636	
	(0.0618)		(0.8009)	
$\alpha_1 = \alpha_2$	4.3483**		1.7564	
	(0.0370)		(0.1851)	
$\beta_1 = \beta_2$	84.6471***		38.8884***	
	(0.0000)		(0.0000)	
$\gamma_1 = \gamma_2$	0.0783		0.0684	
	(0.7796)		(0.7936)	
$\delta_1 = \delta_2$	2.6231		2.2305	
	(0.1053)		(0.1353)	

Notes: The estimated Markov-regime Switching model is represented by equation: $y_{WTI,t} = \omega_{s_t} + \alpha_{s_t} y_{WTI,t-1} + \beta_{s_t} y_{OVX,t} + \gamma_{s_t} y_{USD,t} + \delta_{s_t} y_{SPX,t} + \varepsilon_t$. The sample period of daily observation runs from January 1, 2018 to December 31, 2021. Significance at 1, 5 and 10% level is denoted by ***, **, and *, respectively. The hypothesis tests for equal coefficients are based on the Wald test following the χ^2 distribution. Figures in round brackets represent probability values.

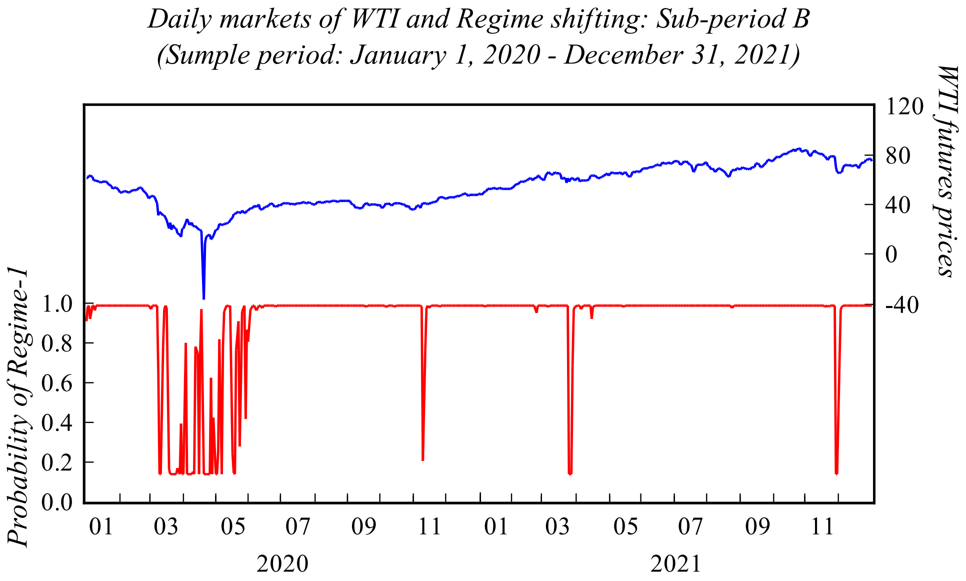
Figure 3. Probability of Regime – 1 (Subperiod A- Jan. 2018 – Dec. 2021)

Daily markets of WTI and Regime shifting: Sub-period A
(Sumple period: January 1, 2018 - December 31, 2019)



Judging from the estimated probability values reported in Figure 3, it is Regime-1 that seems to predominate over subperiod A. The regime switches are not likely to take place as the decrease in the likelihood of Regime 1 remains above the fifty-percent threshold probability value. Thus, it is the Regime with strong negative correlation with volatility expectations that is more likely to prevail. Similarly, the evidence from Figure 4, which reports the Regime-1 probability for subperiod B, suggests that there are frequent regime shifts in association with the precipitous fall in futures prices below zero. A shift toward Regime 2 implies that futures returns are governed by stronger negative correlation with changes in the OVX index. This suggests that higher levels of volatility expectations are conducive to even lower futures returns. Apart from the short period of negative future pricing, it is Regime-1 that tends to prevail with weaker but still significantly negative correlation with volatility expectations.

Figure 4. Probability of Regime – 1 (Subperiod B- Jan. 2020 – Dec. 2021)



In order to further examine the robustness of a two-state Markov-regime switching models to changes in the sample period, the focus is made on subperiod C from July 2008 to June 2010, which may be in part reflective of the effects of the U.S. credit crisis on the inner dynamics of oil futures returns and their relationship with volatility expectations and alternative asset markets. The evidence from Table 4, which reports the estimation of the regime switching model with a two-state Markov chain, indicates that both regimes are characterized by statistically insignificant drifts ω_s and autoregressive terms α_s. However, futures returns are likely to be governed by strong negative correlation with dollar index returns γ_s and positive correlations with equity returns δ_s under both regimes. In contrast, a shift from Regime-1 to Regime-2 is likely to result in a strong negative correlation between futures returns and volatility expectations fading away. However, the aggregate evidence from Wald tests of the null hypothesis of equal coefficients suggests that it is difficult to distinguish between these Markov regimes, and that given their similar properties, it is more likely that the two regimes collapse into a single one with significantly negative sensitivity to dollar index returns $\gamma < 0$, positive sensitivity to $\delta > 0$, and a more likely negative correlation with changes in the OVX index $\beta \leq 0$. Thus, it is clear from the estimation results for subperiod C that periods of financial instability can weaken the correlation of futures returns with volatility expectations. Under higher levels of uncertainty, an increase in oil volatility expectations may not be conducive to diminishing futures returns. It is rather the linkage between oil futures returns and financial markets that gains more significance.

Increasing oil futures returns are more likely to result from lower dollar valuation and higher equity.

Table 4. Markov-regime switching model results (Subperiod C estimated period).

Model parameters	Subperiod C (Jul. 2008 – Jun. 2010)	
	Markov-Regime 1	Markov-Regime 2
ω	0.0006 (0.4797)	−0.0008 (0.8519)
α	0.0621 (0.1126)	−0.0018 (0.8062)
β	−0.1402*** (0.0000)	−0.0958 (0.1062)
γ	−1.7029*** (0.0000)	−1.1439** (0.0169)
δ	0.3553*** (0.0000)	0.4894*** (0.0006)
$Log(\sigma)$	−4.1663*** (0.0000)	−2.9762*** (0.0000)
Log likelihood	1220.131	
AIC	-4.6212	
Hypothesis Tests		
$\omega_1 = \omega_2$	0.1054 (0.7454)	
$\alpha_1 = \alpha_2$	0.8807 (0.3480)	
$\beta_1 = \beta_2$	0.3969 (0.5287)	
$\gamma_1 = \gamma_2$	1.0965 (0.2950)	
$\delta_1 = \delta_2$	0.5650 (0.4523)	

Notes: The estimated Markov-regime Switching model is represented by equation: $y_{WTI,t} = \omega_{s_t} + \alpha_{s_t} y_{WTI,t-1} + \beta_{s_t} y_{OVX,t} + \gamma_{s_t} y_{USD,t} + \delta_{s_t} y_{SPX,t} + \varepsilon_t$. The sample period of daily observation runs from July 1, 2008 to June 30, 2010. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively. The hypothesis tests for equal coefficients are based on the Wald test following the χ^2 distribution. Figures in round brackets represent probability values.

4-3. Robustness's check

This paper assumes that there is a two-state, lower volatility under bullish markets and higher volatility under bearish markets, in the WTI futures market that reflect market uncertainty, and conducted an empirical analysis using the Markov-regime switching model, a nonlinear model, to be determined whether the correlation between WTI returns and OVX daily change performs with a two-state of the market depending on fluctuation of markets. Furthermore, it is possible to consider empirical analysis from a different perspective without taking into account the inner market states. The approach is using a linear model to analyze the correlation between WTI returns and OVX daily fluctuations before and after the structural change date, respectively. Thus, in this section, it is used the autoregressive distributed lag (ARDL) model, one of the linear models, to test whether the empirical analysis demonstrated in this paper is robust. This section also examines whether especially WTI and OVX have a cointegration relationship in each period before and after the structural change using the bounds testing approach of Pesaran et al. (2001).

At first place, an explanation of the empirical model used in the linear model estimation is provided. Equation [10] is based on the general ARDL model and incorporates variables similar to those in Equation [2] used in this paper.

$$y_{WTI,t} = \omega + \sum_{k=1}^{m} \alpha_k y_{WTI,t-k} + \sum_{k=0}^{m} \beta_k y_{OVX,t-k} + \sum_{k=0}^{m} \gamma_k y_{USD,t-k} + \sum_{k=0}^{m} \delta_k y_{SPX,t-k} + \varepsilon_t \qquad [10]$$

where the disturbance terms are white noise distributed with $\varepsilon_t \sim i.i.d.N(0,\sigma^2)$. m is lag up to 1, 2, ...,8, where m is selected the optimal lag length by the AIC. Then, in order to estimate whether all variables, WTI returns, OVX daily changes, Dollar index daily changes and S&P500 index returns, have a long-run relationship, an extension is made from equation (10) to equation (11), following the method derived by Pesaran et al. (2001). Equation (11) can be expressed as follows:

$$\Delta y_{WTI,t} = a_0 + \sum_{i=1}^{m} a_{1,i} \Delta y_{WTI,t-i} + \sum_{i=0}^{m} a_{2,i} \Delta y_{OVX,t-i} + \sum_{i=0}^{m} a_{3,i} \Delta y_{USD,t-i} + \sum_{i=0}^{m} a_{4,i} \Delta y_{SPX,t-i}$$
$$+ a_5 y_{WTI,t-1} + a_6 y_{OVX,t-1} + a_7 y_{USD,t-1} + a_8 y_{SPX,t-1} + \varepsilon_t \qquad [11]$$

where Δ is the first difference operator, a_0, a_1, a_2,..., a_7 and a_8 are parameters, m is the optimal lag length to be used for estimation selected by AIC. The bounds testing approach is based on the F-Statistic and is first of the ARDL cointegration method. The null hypothesis test of no cointegration, $(H_0: a_5 = a_6 = a_7 = a_8 = 0)$, will be performed by equation [11]. Following Pesaran et al. (2001), it is computed two sets of critical value for a given significance level. On set assumes that all variables are I(0) and the other set assumes all variables are I(1). There are three cases which will be obtained. Case one, if the estimated F-Statistic exceeds the upper critical value, the null hypothesis is rejected. Case two, if the estimated F-Statistic is between the upper critical value and lower critical value then the testing becomes inconclusive. Case three, if the estimated F-Statistic is below the lower critical value, it suggested no cointegration among all variables.

As noted in section 4.2, the result from Chow test of structural break indicates that the date on which the existence of structural break is December 25, 2019 and it can be regarded as approximately equal to the base point of dividing subperiods A and B. Therefore, it is performed estimation using equation (10) and equation (11) in sub-periods A and B to verify the change in the correlation between WTI returns and OVX daily changes before and after structural change and to test whether there is a long-run relationship between all variables.

Table 5 summarizes the results estimated in subperiod A using equation (10) , which reflects the optimal lag length selected by AIC and the results of the bounds test for examining long-run relationship between all variables using equation (11). The estimated result with equation [10] for subperiod A indicates that contemporaneous to three periods earlier OVX daily changes are weakly negatively correlated with WTI returns. The absolute value of the t-value is largest for the contemporaneous OVX daily change, suggesting that the contemporaneous period of OVX daily changes is more influential than the other lags to WTI returns where time t. Also, the results of the bounds testing with equation [11] indicates that estimated F-Statistic exceeds upper critical value, it means that it is rejected the no levels of relationship at the 1% significance level (F-Statistic), suggesting there is a cointegration relationship between all variables in subperiod A.

Table 5. Results of Subperiod A estimated with ARDL modelling and the bounds test.

Model parameters [ARDL (5,3,2,0)]	Subperiod A (Jan. 2018 – Dec. 2019) Coefficient	t-Statistic
ω	0.0007	0.8380
α_{t-1}	−0.1567***	−3.5950
α_{t-2}	−0.0658	−1.4974
α_{t-3}	−0.0814*	−1.8818
α_{t-4}	0.0582	1.4148
α_{t-5}	0.0733*	1.7949
β_t	−0.1010***	−6.2670
β_{t-1}	−0.0648***	−4.0226
β_{t-2}	−0.0360**	−2.2070
β_{t-3}	−0.0317*	−1.9481
γ_t	−0.2385	−0.9302
γ_{t-1}	−0.5504**	−2.1447
γ_{t-2}	−0.4391*	−1.7066
δ_t	0.2806***	2.9526
Log Likelihood	1340.482	
AIC	-5.0823	
F-Bounds Test (At the 1% significance level)		
F-Statistic	I (0)	I (1)
29.9258	3.65	4.66

Notes: The estimated ARDL model is represented by equation [10]:
$y_{WTI,t} = \omega + \sum_{k=1}^{m} \alpha_k y_{WTI,t-k} + \sum_{k=0}^{m} \beta_k y_{OVX,t-k} + \sum_{k=0}^{m} \gamma_k y_{USD,t-k} + \sum_{k=0}^{m} \delta_k y_{SPX,t-k} + \varepsilon_t$.
The sample period of daily observation runs from January 1, 2018 to December 31, 2019. Significance at 1, 5 and 10% level is denoted by ***, **, and *, respectively. The hypothesis test of cointegration for all variables is based on the bounds testing with equation [11]:
$\Delta y_{WTI,t} = a_0 + \sum_{i=1}^{m} a_{1,i} \Delta y_{WTI,t-i} + \sum_{i=0}^{m} a_{2,i} \Delta y_{OVX,t-i} + \sum_{i=0}^{m} a_{3,i} \Delta y_{USD,t-i} + \sum_{i=0}^{m} a_{4,i} \Delta y_{SPX,t-i} + a_5 y_{WTI,t-1} + a_6 y_{OVX,t-1} + a_7 y_{USD,t-1} + a_8 y_{SPX,t-1} + \varepsilon_t$.

From the estimation results for subperiods A and B using the linear ARDL model, it can be observed that the correlation between WTI returns and OVX daily changes changed with the occurrence of Covid-19, which is consistent with the empirical results in this paper. In addition, the fact that a cointegration relationship is established in both subperiods from the results of the using Pesaran et al. (2001)'s bounds test suggests that even with structural changes, there is the long- run relationship, which is an important point in the crude oil market. Thus, the empirical results of this paper can be regarded as robust because the change in the correlation between WTI returns and OVX daily changes before and after the structural change can also be observed in the estimation using the linear model and is consisted with the results of this paper.

5. Conclusions

The present study provides new empirical evidence on the stochastic behavior of energy futures returns based on the estimation of Markov-regime switching models. Given the nature of energy markets, the demand and supply functions are intrinsically linked with the real economy and perceptions of economic uncertainty, but there is growing literature about stronger linkages with the financial economy as well. The focus in this paper is placed on the empirical issue of whether the inner dynamics and correlation structures of oil futures with alternative asset markets are governed by different regimes that reflect changes in the underlying demographic, macroeconomic and social conditions. The empirical evidence suggests that oil futures returns tend to be governed by different Markov-regimes, which invariably exhibit negative correlation with volatility expectations which reflect the shifting fear factor dynamics. Thus, market perceptions of heightened economic uncertainty reflected by increased volatility expectations are conducive to diminishing futures returns, irrespective of the prevailing regime.

The nonlinear dynamics of oil futures returns can be altered, however, by significant events such as the onset of financial crises and disease outbreaks as well as government policy responses. There is, indeed, evidence that the economic lockdowns in response to the disease outbreak have the potential of increasing the likelihood of Markov regimes with more pronounced negative correlation of futures returns with changes in expected volatility. Also, periods of financial instability such as the U.S. credit crisis may severe the relationship of oil futures returns with volatility expectations, and strengthen their linkages with currency fluctuations and equity valuation. Thus, Markov regimes switching models have the capacity of capturing changes in the underlying fundamentals, and provide some insights on the changing inner dynamics such as the propensity for mean reversion and long memory for economic shocks that tend to decay over longer time. Regrettably, this paper's shortcomings include the fact that the Markov-regime switching model does not resolve the issues of strict simultaneity and endogeneity between WTI and OVX, which is an issue for future research. Further research may shed light on the non-linear dynamics with time-varying transition probabilities, simultaneity and jump diffusion processes which may better account for the stochastic properties of energy prices.

Chapter 2. Dynamic Correlation Between U.S. Oil and Global Shipping Markets: The Determinants Factors of Fluctuations

1. Introduction

The shipping market is determined by wages for ocean transport on several routes, known as Panama and Cape-size. It is regarded that when the economy improves, the shipping market tends to improve due to increased logistics and trade volume, and vice versa. As such, it is sometimes regarded as a leading indicator of the economy, and has been attracting attention in recent years due to expectations that the market can reflect the real economy and business cycles. In addition, the shipping market is closely related to the crude oil market, from the perspective of fuel costs, which have a direct impact on transportation costs, and is therefore of interest not only to companies involved in marine transportation, but also to investors[4] in the crude oil market. Against this backdrop, research on the correlation between the shipping market and the crude oil market is gradually being developed, mainly from the perspective of risk management.

However, while empirical analyses have been conducted on the correlation and causality between the oil market and BDI, the results of these correlations and causality are not settled, and considerations such as global events, shocks, or completely different external information may be causes at work are often discussed. In particular, there have been a number of studies analyzing dynamic conditional correlations between two markets using diagonal-BEKK model by Engle and Kroner (1995) and Dynamic Conditional Correlation (DCC) model by Engle (2002), but unfortunately, most of them have not examined the factors that cause dynamic conditional correlations to fluctuate.

Hence, the purpose of this paper is to analyze what is behind the dynamic conditional correlation that exists between the crude oil market and shipping indexes. Through this analysis, it is hoped that this paper will provide one part of answer to some of the questions and arguments that have not been clarified in previous studies. That is why, this paper will attempt to analyze the factors behind the dynamic conditional correlation between the crude oil market and the shipping market, i.e., the markets that are contemporaneously correlated with the estimated dynamic correlation are defined as the determinant factors of fluctuation, and what kind of markets are the determinant factors of fluctuation.

The empirical analysis using a diagonal-BEKK model with monthly data for about 15 years

[4] Most analyses of energy markets, including crude oil, involve financial markets (stock and exchange markets) and are discussed from the standpoint of commodity markets as investment targets. Nevertheless, energy markets are an important component of economic activity, and in light of recent social conditions, such as a rapid decarbonization of society, such as the Ukrainian progression to review energy policy and allow investment in nuclear power generation, empirical studies that reflect the conditions of the real economy would be more informative in analyzing energy markets. While reflecting the real economy is practically difficult, there are alternative ways to describe the economy by using shipping and trade volumes. Among these, the shipping index is one that is relatively easy to use and data is available to anyone, and in fact, empirical analysis of the shipping index and the crude oil market has already been conducted.

from 2007 to 2023 reveals the existence of a dynamic conditional correlation between the monthly returns of the U.S. crude oil market and the monthly returns of a shipping index. The analysis also reveals that the determinants of the dynamic conditional correlation are not geopolitical risk or global stock markets, but tend to be correlated with risk-related indices such as the policy uncertainty risk or fear indices etc. Accordingly, the empirical results suggest that the dynamic conditional correlation between the two markets is influenced by risks such as policy-related uncertainty, market returns on U.S. stock market and changes in producer prices, and is expected to be one of the pieces to solve the puzzle of irregular correlation and causality between crude oil and shipping markets in most of the previous studies. In addition, while the main task of previous studies is to estimate dynamic conditional correlations, the attempt in this paper is an empirical result that can provide new possibilities for those who study the relationship between the crude oil and shipping markets.

Finally, an introduction to the structure of this paper is provided. The next section, Section 2, provides an explanation of the shipping index and related indices and an introduction to the earlier studies on crude oil and shipping indexes. In Section 3, explanations are provided for the derivation of the monthly return dynamics for each market and the empirical model, the diagonal-BEKK model. Section 4 presents tests of the distributional properties of the sample data and the unit root process, followed by an examination of the estimation results from the empirical models in Section 5. Section 6 concludes the paper.

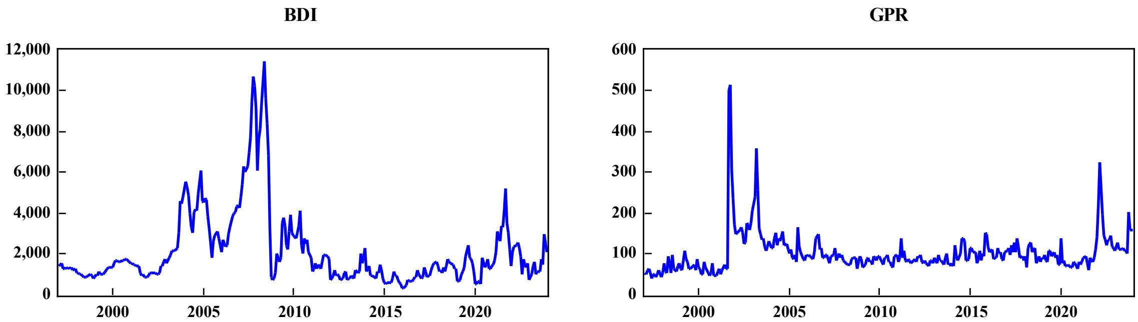
2. Literature Review

In Section 2, the Baltic Shipping Index (BDI), which is often used in empirical analyses related to the oil market and shipping indices, and the Geopolitical Risk Index (GPR), which is considered to be closely related to the oil market and shipping indices, will be introduced using time series data and other data. The presentation will then introduce earlier empirical studies on the relationship between the oil market and shipping indexes, and explore the room for novelty.

2-1. Global shipping markets and Geopolitical risk index

The BDI, one of the subjects of this paper's analysis, is an index of wages per shipping route for ocean transport calculated and published by the Baltic Shipping Exchange in the U.K. based on a specific formula, and is considered one measure of trends in freight rates in the shipping market. Figure 1 (left) plots the monthly data of the index in chronological order from January 1997 to December 2023. From Figure 1, it can be seen that the BDI has remained flat except for a specific timing period. The first is from 2003 to 2005, the second is from 2007 to 2009, and the third is from 2020 to 2022. Global events in 2003-2005 included the Iraq War, the surge in oil prices and the global outbreak of avian influenza. A very distinctive event in 2007-2009 was the global financial shock triggered by the U.S. real estate market and related debt markets, an event known as the Global Financial Crisis or Lehman Shock. The events occurring in 2020-2022 include the global spread of the Covid-19 virus and the resulting global economic stagnation, as well as Russia's progress in Ukraine. It is thought that the reason for the remarkable surge in shipping indexes during these periods cannot be explained by mere fluctuations in the supply-demand relationship[5] in the shipping market alone. In other words, there may be some event or events that have nothing to do with the supply-demand relationship that are affecting the shipping market. Exploring this factor will hopefully help us in our future research on global economic trends.

Figure 1. Time-series of BDI and GPR monthly data (1997 ~ 2023)



Next, let us discuss some aspects of the GPR, which is an indicator of the degree of geopolitical risk that would increase if, for example, a war broke out in a certain country and the situation became unstable. It is therefore similar to the Volatility Index (VIX) published by the CBOE, which quantifies the degree of fear and uncertainty about the future of the stock market. The GPR was produced by the work of Caldara and Iacoviello (2022) and is now readily available on their website. The most important feature of this index is that it is a time-series data set that quantifies the tensions generated by world events, such as wars and outbreaks of terrorism, based on specific conditions[6].

Therefore, the GPR seems to highlight armed actions associated with political or religious conflicts. Furthermore, it is obvious that energy resources such as crude oil are greatly influenced by the situation in the producing countries, and the situation in the Middle East, which boasts a particularly large market share, is said to have a non-negligible impact on prices. It can thus be regarded as an indispensable factor in the analysis of the crude oil market, and it can be assumed that it is also related to the determinants of fluctuations in dynamic correlations, which is the objective of this paper. Indeed, both Khan et al. (2021) and Monge et al. (2023) have conducted empirical analyses using GPR as an explanatory variable for the crude oil market and BDI, providing that it is a statistically significant correlation[7].

Incidentally, as with the BDI, the monthly data for the GPR from January 1997 to December 2023

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[5] In this case, the relationship between vessel volume and freight rates on each route, etc.

[6] The highest value in the GPR is defined as the September 11, 2001 terrorist attacks on the World Trade Center by the Islamic extremist group al-Qaeda (commonly known as 9/11).

[7] Their study points out that GPR is the market behind the crude oil market and BDI, but suggests that the speed of propagation between the markets is not equal.

are plotted in time-series order in the right-hand side of Figure 1. As with the BDI, there is almost no significant fluctuation in the GPR except for a specific period. The specific periods are 2001, 2003, and 2022. All of these periods coincide with periods of social instability, in order from oldest to youngest: 9/11, the Iraq War, and the Ukraine crisis. Conversely, during the global financial crisis and the Covid-19 expansion, the GPR did not fluctuate as much as in the previous three periods.

2-2. Earlier studies for correlation between oil and shipping markets

Although studies of the shipping market itself have been conducted for many years, most of them have been based on actual demand, such as the relationship between freight rates and transportation costs, and the optimization of route selection. Hence, it seems that there is still room for research that adopts an economic approach, compared to research on so-called financial markets such as the stock and bond markets. In this paper, regarding the shipping market in relation to the crude oil market, relatively new empirical studies will be introduced, and the research trends will be summarized.

To begin with, let us discuss studies that focus exclusively on BDI. In fact, there are many studies that highlight only BDI, such as Kavussanos (1996), Kavussanos and Nomikos (1999), Kavussanos and Alizadeh-M (2001), Kavussanos and Nomikos (2003), Kavussanos and Visvikis (2004). These introduced studies analyzed the price fluctuation factors of BDI and dry cargo vessels' freight rates using various approaches. Recently, analyses involving financial markets and empirical studies using financial approaches have been dealt with, and it can be seen that researchers specializing in the shipping market also have a very strong interest in the relevance of other markets. It should be noted that a notable feature of these studies is that they are cited in every paper in the empirical analysis of the shipping freight market, which is very informative. In addition to these studies, other studies such as Tsouknidis (2016) and Bandyopadhyay and Rajib (2023) have recently appeared[8].

Next, studies on shipping markets or shipping rates and crude oil markets, which are the subject of this paper, will be introduced. Studies on the relationship between the shipping market and the crude oil market have often used BDI and Brent crude oil for empirical analysis due to their geographical nature. This may be attributed to the fact that the exchanges that publish shipping indices are located in the U.K., and it is assumed that the analysis is conducted with the Brent crude oil market in the expectation of a closer relationship between the two markets.

For example, the study by Ruan et al. (2016) analyzed the cross-correlation between the spot price of Brent crude oil and BDI and found that the cross-correlation existed in the short term but did not produce the expected results in the long term. The study by Choi and Yoon (2020) also

[8] Tsouknidis (2016) analyzes freight rates on the four shipping routes on which the shipping index is based, using Engle's (2002) DCC model. On the other hand, Bandyopadhyay and Rajib (2023) find asymmetric causality between spot prices and BDI for major dry bulk commodities such as aluminum, coal, and wheat, but do not mention causality with crude oil or natural gas. Both studies are characterized by the use of analytical techniques commonly used in financial market analysis.

analyzed tail dependence rather than cross-correlation and noted that the results were different in the long and short term. Thus, previous studies suggest that the relationship between Brent crude oil and BDI is not consistent but has a time-varying component. There is thus room for research to determine whether the correlation between the U.S. crude oil market and the BDI is similar to that of Brent crude oil. Other approaches exist that focus on volatility rather than price returns. One study that focuses on the transmission of volatility between the shipping and crude oil markets is Riaz et al. (2023). Based on empirical results, they consider that spillovers between markets are more pronounced during the financial crisis and during COVID-19 and 2014-2016, which were difficult periods for the shipping industry due to the large fluctuations in oil prices.

Nevertheless, it seems that BDI is often employed as one of the explanatory variables only to validate something rather than as an analysis between BDI and the crude oil market, as in the studies by Giannarakis et al. (2017) and Han et al (2020). The reason for this may be that there is a common understanding among investors that BDI itself is a leading indicator of economic trends. Indeed, studies such as Lin and Sim (2013), Bildirici et al. (2015), and Gao et al. (2023) have discussed whether BDI can be considered a leading indicator of economic trends, suggesting that interest in BDI is diverse.

One notable study in this research trend is that of Sun et al. (2014). Their study reveals a positive correlation between the Baltic Dry Tanker index and crude oil prices under certain conditions, but on the other hand, they point out that the complex structure of the two markets makes it preferable to seek a dynamic correlation rather than a single analysis. Also, Kim and Park (2019) conduct an empirical analysis of the lead-lag relation between prices of major commodities, including crude oil, imported into Korea and the corresponding ocean freight rates. The empirical results point out that Granger causality and the lead-lag relation vary over the sample period. From this empirical result, it can be inferred that the correlation between U.S. crude oil and shipping indices may not be consistent as well. Other studies exist, such as Lin et al. (2019), who conduct an empirical analysis of whether BDI affects each of the equity, currency, and commodity markets during specific crises in the United States and China. The study results suggest that the shipping and oil markets are more relevant during specific shocks. Therefore, if following the studies of Sun et al. (2014) and Kim and Park (2019), the multivariate GARCH model is a powerful analytical method, as it can estimate time-dependent correlations, one of the dynamic correlations. Furthermore, the matrix BEKK model, which is said to be thrifty in empirical analysis, is expected to be an effective candidate approach in the analysis.

Indeed, there are prior studies that conduct empirical analyses using diagonal-BEKK models or the same type of DCC models, such as the recent study[9] by Chen et al. (2023). Most

[9] As a supplement, let us introduce a study that uses a completely different approach from the previous studies introduced: the study by Chen et al. (2017), which uses a multifractal structure to analyze the long-run persistence of WTI and BDTI. This study analyzes cross-correlations using a multifractal structure and provides evidence suggesting that WTI and BDTI are still strongly long-run persistent and multifractal cross-correlated, although the influence of the fat-tail distribution was strengthened during the financial crisis. In other words, the possibility that certain correlations may exist over the long term cannot be ruled out. Hence, it is of great significance to explore cross-

of these studies tend to target the estimation of dynamic conditional correlations, and are conducted from various angles, extensions of empirical models addressed in previous studies, or estimation with novel models incorporating model equations from different fields. While this has certainly contributed to improving the accuracy of dynamic correlation estimation, there seems to be no study that addresses the question of why the estimated dynamic conditional correlations show such changes. Some earlier studies are discussed that the estimated dynamic conditional correlations between oil market and BDI market may be fluctuating due to some external factor, for example, financial shocks or geopolitical changes. Therefore, in this paper, it is expected that there is room for novelty in the exploration of the factors that cause variation in this dynamic correlation, and will attempt to analyze what determinants of variation exist.

3. Empirical Modeling

Section 3 first discusses the two price dynamics needed to estimate the matrix BEKK model, the price dynamics of monthly returns on U.S. crude oil futures (WTI) and BDI monthly returns. Subsequently, it will discuss the matrix BEKK model and the regression equations for analyzing the determinants factors of fluctuation on DCC.

3-1. Modeling for U.S. crude oil futures and global shipping markets

In general, the dynamics of pricing models are such that prices are determined by historical data and information brought to the market, known as market noise. However, it is difficult to say that these two factors alone are sufficient to explain the dynamics of pricing models, and many studies have conceptualized various pricing modeling approaches and verified them through empirical analysis. In this paper, considering the recent social situation, price dynamics attempt to construct based on the assumption that long-term real economy factors such as geopolitical risk, economic uncertainty, and economic trends affect the crude oil and shipping markets. This is a very interesting point because it is not common in previous studies to incorporate qualitative factors into model equations, especially since there is no idea where they stand in the crude oil market. Therefore, this section first describes the derivation process for the two types of price dynamics, WTI and BDI, respectively. Note that most indices representing the real economy tend to be treated as annual, quarterly, or monthly data, and the Producer Price Index (PPI), which is a candidate for modeling, is also published in monthly data. This is why monthly data will be used for all time-series data related to the modeling. The description and distributional properties of each monthly data set are described in Section 4 below.

First, a derivation of the price dynamics of WTI monthly returns will be presented. It has been pointed out in many studies, including Pindyck (2001), that in general, prices in the crude oil market fluctuate depending on the production volume of oil-producing countries and the balance between supply and demand. In this paper, however, pricing modeling would like to

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correlations. Since this paper focuses on the analysis of the determinants of variation in dynamic correlations, research on cross-correlations is a topic for future study.

attempt a different construction from conventional price dynamics, taking into account the fact that this is a long-term analysis. Huang et al. (2021) investigated the nonlinear dynamic correlation between GPR and oil prices based on high frequency data using nonlinear Granger causality. The empirical results show that GPR returns have a relatively weak one-way nonlinear Granger causality with respect to crude oil returns. Given this, it can be assumed that the crude oil market is affected by fluctuations in geopolitical risk, such as discord in oil-producing countries and trade frictions among major economic powers. In addition, since WTI, the subject of our analysis, is the U.S. crude oil benchmark, if expectations for the crude oil market also change depending on the direction of energy policy[10], it can be assumed that the crude oil market may also be affected by policy uncertainty risk. These relationships can be expressed in the model equation for long-term monthly returns as in equation (1) as follows.

$$y_{WTI,t} = \omega_1 + \alpha y_{GPR,t-1} + \beta y_{EPU,t-1} + \varepsilon_1 \tag{1}$$

where, $y_{WTI,t}$ represents the monthly returns of WTI at time t, $y_{GPR,t-1}$ represents the monthly change in GPR at time t-1, and $y_{EPU,t-1}$ represents the monthly change in EPU at time t-1. ω_1 is the drift term in equation (1), and ε_1, which represents the error term, is assumed to follow a standard normal distribution. α and β are the coefficients of each explanatory variable. Each monthly returns and monthly change in equation (1) are calculated by the log returns or log change in each monthly data, as shown in equation (2) as follows.

$$y_{i,t} = \log\left(\frac{price_{i,t}}{price_{i,t-1}}\right), i = WTI, GPR, EPU \tag{2}$$

However, equation (2) alone could have a strong qualitative component and could result in a statistically inadequate model equation, so to avoid this, it would be desirable to incorporate time-series data on financial markets as an additional control variable. Many empirical studies on the crude oil market have already employed a method that combines exchange rates and bond yields, and time-series data on financial markets can be expected to function adequately as a control variable. There are several candidates, but if long-term analysis is taken into account, the yield on the 10-year U.S. Treasury bond yield (US10Y) is probably the preferred choice. Based on the above, equation (2) will be incorporated the monthly returns of US10Y: $y_{US10Y,t} = \log\left(price_{US10,t}/price_{US10Y,t-1}\right)$ as a control variable to obtain the price dynamics of the monthly WTI returns. And it can be expressed as in equation (3) as follows.

$$y_{WTI,t} = \omega_1 + \alpha y_{GPR,t-1} + \beta y_{EPU,t-1} + \theta y_{US10Y,t-1} + \varepsilon_1 \tag{3}$$

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[10] For example, if the president is a Democrat, the oil market will contract in consideration of a decarbonized society, but if the president is a distinctive Republican, the policy will change to one that increases energy production, etc.

where, θ is the coefficient of monthly returns for US10Y. The other definitions follow from equation (1) and (2). As a hypothesis regarding the sign of each coefficient, if an increase in each risk has an upward effect on the U.S. oil price, the same can be considered to be true on a monthly returns basis, and the coefficients α and β of each explanatory variable are expected to have a positive sign. In addition, given the relationship between the economy and government bond yields and the fact that crude oil prices are also expected to rise in times of economic boom due to supply chain effects, the coefficient θ on the monthly returns of US10Y is expected to have a positive sign.

Second, price dynamics of BDI monthly returns are derived in the same manner as in equation (3): the BDI is indexed from the freight rates of multiple existing shipping routes, as described in Section 2. Therefore, it is obvious from the relationship between supply and demand that freight prices change in proportion to the volume of ship operations, as pointed out in the study by Açık and Kayıran (2022). And fuel costs are added to ship freight rates as a cost. In other words, the higher fuel cost is directly transferred to the freight price, which in turn increases the price. Technically speaking, the fuel used on most ships is derived from heavy oil, which is refined from crude oil under certain conditions. Therefore, assuming that fluctuations in the crude oil market propagate indirectly from fuel costs to freight prices, they may eventually affect the BDI, which is an index. This can be expressed as the price dynamics of the long-term BDI monthly returns as in equation (4) as follows.

$$y_{BDI,t} = \omega_2 + \gamma y_{WTI,t-1} + \varepsilon_2 \tag{4}$$

where, ω_2 is the drift term in the price dynamics of BDI monthly returns, and ε_2, which represents the error term, is assumed to follow a standard normal distribution. The dependent variable $y_{BDI,t}$ represents the BDI monthly returns at time t. The BDI monthly returns are obtained from the same equation as in equation (2) and are as in equation (5);

$$y_{BDI,t} = \log\left(\frac{price_{BDI,t}}{price_{BDI,t-1}}\right) \tag{5}$$

It is also assumed that the shipping market is closely related to business conditions, in other words, to the volume of trade and transportation by ship, and that factors related to business trends cannot be ignored. Therefore, in equation (5), the variable that expresses the business trend is to be incorporated. Various periodicals, including FRED and OECD, have published indicators of economic trends, but in this paper, due to the nature of energy, an indicator that focuses on industry will be selected as a candidate target. One such candidate is the PPI. The Producer Price Index, which is measured on the basis of primary commodities such as iron ore, can be assumed to have a particularly close relationship with the economy, and the monthly change in PPI: $y_{PPI,t} = \log\,(price_{PPI,t}/price_{PPI,t-1})$ is an additional variable. Equation (6), which is added to Equation (5) with the PPI monthly change as a new explanatory variable, can be expressed as follows.

$$y_{BDI,t} = \omega_2 + \gamma y_{WTI,t-1} + \delta y_{PPI,t-1} + \varepsilon_2 \tag{6}$$

where, δ is the coefficient of the PPI monthly change at time t-1. The definition of each variable, including ω_2, is assumed to follow equation (4). Hypothesis on the signs of the two coefficients γ and δ is established. If changes in crude oil prices have a positive impact on ship fuel costs, γ is expected to be positively correlated, since it can be assumed to be a factor that indirectly increases the shipping index. If it is also assumed that the revitalization of the real economy associated with a booming economy increases the volume of marine transportation, then δ is expected to be positively correlated based on the supply-demand relationship in the shipping market.

3-2. Empirical modeling with diagonal-BEKK model

A diagonal-BEKK model used in the equations for estimating conditional dynamic correlations from the respective price dynamics equations for WTI monthly returns and BDI monthly returns is described in this section. This paper follows the conventional classical multivariate GARCH model, the BEKK model of Engle and Kroner (1995), rather than an empirical analysis with specific additional model building. The model equation can be expressed as in equation (7) as follows.

$$H_t = C + A(\varepsilon_{t-1}\varepsilon'_{t-1})A' + B(H_{t-1})B' \tag{7}$$

where, H_t is a 2×2 conditional variance covariance matrix and matrices of A and B are again restricted to being diagonal (diagonal parameters). C is an indefinite matrix. Also, ε_{t-1} is a 2×1 disturbance vector. The symbol of $'$ in the upper right corner of the variable means transposition of the matrix. In addition, each variable H_t, A, B, and C can be expanded as in the following equation (8).

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix}; C = \begin{bmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{bmatrix}; A = \begin{bmatrix} a_{11} & a_{12} \\ a_{12} & a_{22} \end{bmatrix}; B = \begin{bmatrix} b_{11} & b_{12} \\ b_{12} & b_{22} \end{bmatrix} \tag{8}$$

The value obtained by dividing the conditional covariance: $Cov(y_{WTI,t}, y_{BDI,t}) = h_{12,t}$ of WTI monthly returns and BDI monthly returns estimated by equation (7) by the product of their respective standard deviations: $Std.Dev._{y_{WTI}}\, Std.Dev._{y_{BDI}}$ is the dynamic conditional correlation (DCC_t)、 as in equation (9) as follows.

$$DCC_t = \frac{Cov(y_{WTI,t}, y_{BDI,t})}{Std.Dev._{y_{WTI}}\, Std.Dev._{y_{BDI}}} \tag{9}$$

3-3. Empirical modeling for determinants factors of Fluctuations in DCC

Finally, it will describe the regression equation for analyzing what are the determinants of variation for the dynamic correlations estimated from equation (9). In addition, in order to analyze which markets are the determinants factors on DCC in an easy-to-understand approach, three types of groupings will be made, and estimations will be made for each group. The three groupings are (1) Risk Indices, (2) Financial markets, and (3) Economic Trends. (1) Risk Indices are categorized into various risks such as financial risks and uncertainty risks as well as geopolitical risks. Financial markets are categorized as markets related to finance, such as stocks and exchange rates, and economic trends are categorized as business confidence indices and economy-related indices for countries relevant to this empirical analysis. The details of each group are shown in Table 1 below. The regression analysis to analyze the determinants of change shall be estimated for each group and can be expressed as in equations (10), (11), and (12) as follows.

$$DCC_t = \lambda_0 + \lambda_1 GPR_t + \lambda_2 EPU_t + \lambda_3 VIX_t + \lambda_4 NFCI_t \tag{10}$$

$$DCC_t = \phi_0 + \phi_1 y_{SP500,t} + \phi_2 y_{US10Y,t} + \phi_3 y_{USDX,t} + \phi_4 y_{MSCI,t} \tag{11}$$

$$DCC_t = \psi_0 + \psi_1 BCI_{US,t} + \psi_2 BCI_{UK,t} + \psi_3 BCI_{EU,t} + \psi_4 y_{PPI,t} \tag{12}$$

where, each explanatory variable is employed as a contemporaneous model in the regression equations from equation (10) to equation (12). This is a measure to exogenously analyze which market is the determinants factors on estimated dynamic conditional correlation at time t. Thus, it is possible to infer the trend of the determinants of fluctuation by examining the signs of the coefficients of each explanatory variable and whether they have statistically significant correlations.

Table 1. Details of the three groups used to analyze the determinants factors on DCC

① Risk Indices	
Geopolitical Risk Index	GPR_t
Economic Policy Uncertainty Index	EPU_t
Volatility Index	VIX_t
National Financial Condition Index	$NFCI_t$
② Financial Markets	
S&P500※ (SP500)	$y_{sp500.t}$
US10Y Bond Yield※	$y_{US10Y.t}$
U.S. Dollar Index※	$y_{USDX.t}$
MSCI World Index※	$y_{MSCI.t}$
③ Economic Trends	
Business Confidence Indicators US	$BCI_{US.t}$
Business Confidence Indicators UK	$BCI_{UK.t}$
Business Confidence Indicators EU	$BCI_{EU.t}$
Producer Pirce Index※	$y_{PPI.t}$

Note: The marked with ※ are calculated on monthly returns (or monthly changes), not monthly data, for the regression analysis.

3-4. Additional empirical modeling for determinants factors of Fluctuations in DCC

While section 3-3 presented empirical modeling to detect individual aspects of the determinants of DCC, this section describes a different type of modeling. This is because another modeling is needed to estimate the DCC determinants through empirical modeling in order to examine the complexity market case. The model construction again is simple, with one variable extracted from each factor group as the three explanatory variables. In this case, principal component analysis is used to extract one variable from each group. Therefore, a principal component analysis is conducted for each group (risk indices, financial markets, and economic trends), and the variable with the highest loadings is selected without the first principal component (or the second principal component if necessary) and incorporated into the empirical model. The equation is expressed as follows

$$DCC_t = \zeta_0 + \zeta_1 PC1_{risk\ indices,t} + \zeta_2 PC1_{financial\ market,t} + \zeta_3 PC1_{economic\ trends,t} \quad (13)$$

where, the explanatory variable PC1 is assigned the variable with the highest loading among the first principal components estimated by principal component analysis.

Based on the above, there are two types of empirical models addressed in this paper. First, an empirical analysis of the determinants factor of DCC for each group will be conducted using the empirical model in Section 3-3. Subsequently, the empirical model in Section 3-4, which takes a more realistic viewpoint, will be used to examine the determinants of DCC variation in the complex case.

4. Data Properties

Section 4 first introduces the description of the sample data used in the empirical analysis, the sample period, and the distributional properties of each data set, and then examines whether or not a unit root process exists. Then, explanations and distributional properties of the additional samples employ for verification determinants factors on dynamic conditional correlations estimated through the empirical analysis, as well as the existence of a unit root process, are verified.

4-1. Monthly data of samples

The sample data employed in this paper are first described. WTI is the monthly data of the U.S. crude oil futures market, BDI is the monthly data of the Baltic Dry Index, and US10Y is the monthly data of the 10-year U.S. Treasury bond yield. These three time-series data are obtained from Thomson Reuters and Investing.com. The PPI is the monthly data of the Producer Price Index converted in primary commodities and published by the Federal Reserve Economic Data (FRED). The FRED specifies that the index is based on the year 1982 as 100.The GPR and EPU are published in studies by Caldara and Iacoviello (2022) and Baker et al. (2016), and the two time series data were obtained from their respective research websites.

Figure 2 plots the monthly data for each sample as time series data. From Figure 2, the timing of the transition appears to occur at the same time for the four time-series data except for GPR and EPU, suggesting that the sharp decline in 2008 was caused by the global financial crisis, the global financial crisis. Also, the steady increase from 2020 suggests that economic activity, which was stalled by Covid-19, is recovering. On the other hand, the GPR and the EPU are seen to be expressive of their respective concepts. In particular, the GPR indicates that the 9/11 terrorist attacks in the U.S. caused a greater increase in geopolitical risk than the global economic stagnation caused by Covid-19, while the EPU shows a gradual increase in uncertainty risk, as can be seen in Figure 2.

Figure 3 shows the time-series data representation of the monthly log returns for each sample data. It is surprising that the fluctuation range of WTI in the commodity market and BDI in the shipping freight market is large, as well as that of GPR and EPU, which are qualitative indicators. In terms of fluctuation, the shocks in 2008 were large for all four markets except GPR and EPU, but the large volatility in WTI when the futures price fell to negative in April 2020 can be regarded as one of the characteristics of the U.S. crude oil market.

Figure 2. Time-series of six markets monthly data (1997 ~ 2023)

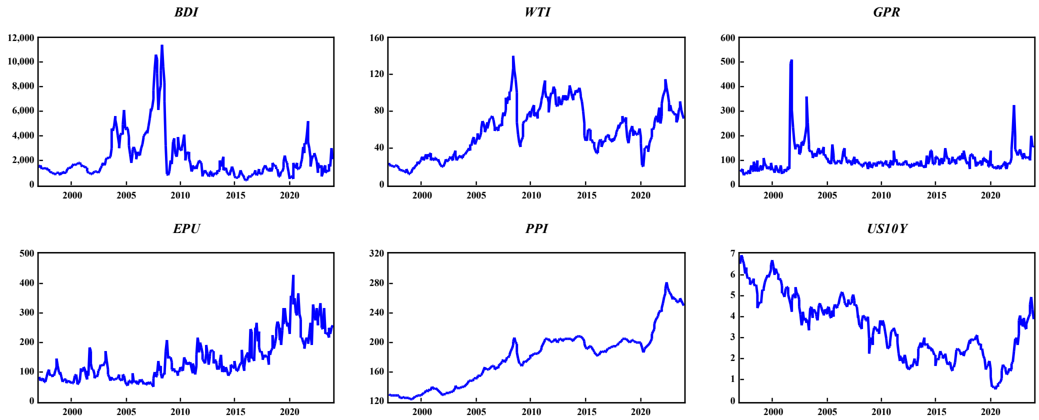
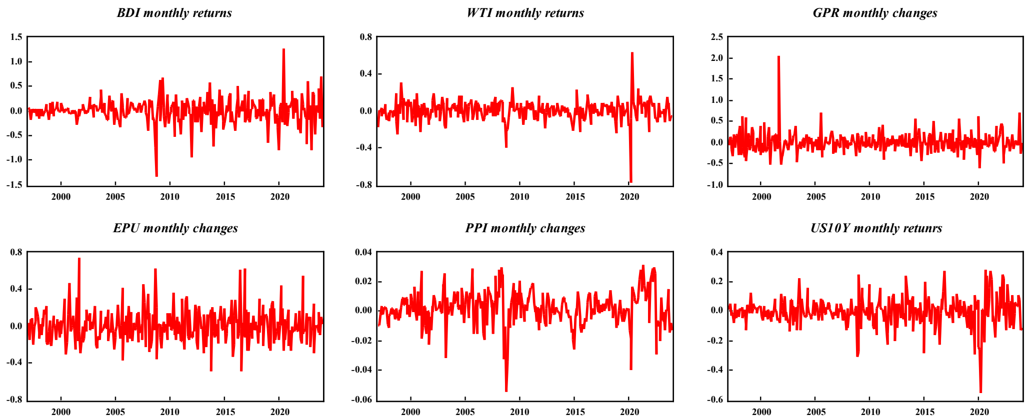


Figure 3. Time-series for monthly returns and changes on six markets (1997 ~ 2023)



Next, the distributional properties of the sample data and monthly returns (and changes) are described. Distributional properties are examined in terms of median, standard deviation, skewness and kurtosis, and the Jarque-Berra test is used to test how close the distribution is to a normal distribution. In addition, an Augmented Dickey-Fuller test (ADF test) was performed to verify whether each sample data is a unit root process. Table 2 summarizes these results, with the upper being the distributional characteristics of each monthly data set and the bottom row being the distributional characteristics of the monthly returns. The ADF test uses three different types of constraints: with trend term, with trend term and intercept and with none of them. And the type of constraint used is indicated by a, b, and c next to the estimated value. The asterisks marks in Table 1 indicate the significance levels, with the 1%, 5%, and 10% significance levels denoted by ***, **, and *, respectively.

The results of the ADF test for the monthly data in the upper part of Table 2 suggest that some of the sample data cannot be rejected as being unit root processes, and that regression analysis using these as variables will lead to sham results. On the contrary, the ADF test for monthly returns in the lower part of Table 2 can reject that all the data are unit root processes, suggesting that a certain level of safety is ensured for the variables used in the empirical analysis. Therefore, it is appropriate to use monthly returns as the empirical model in this paper.

Table 2. Distributional properties of samples and results of stationarity test

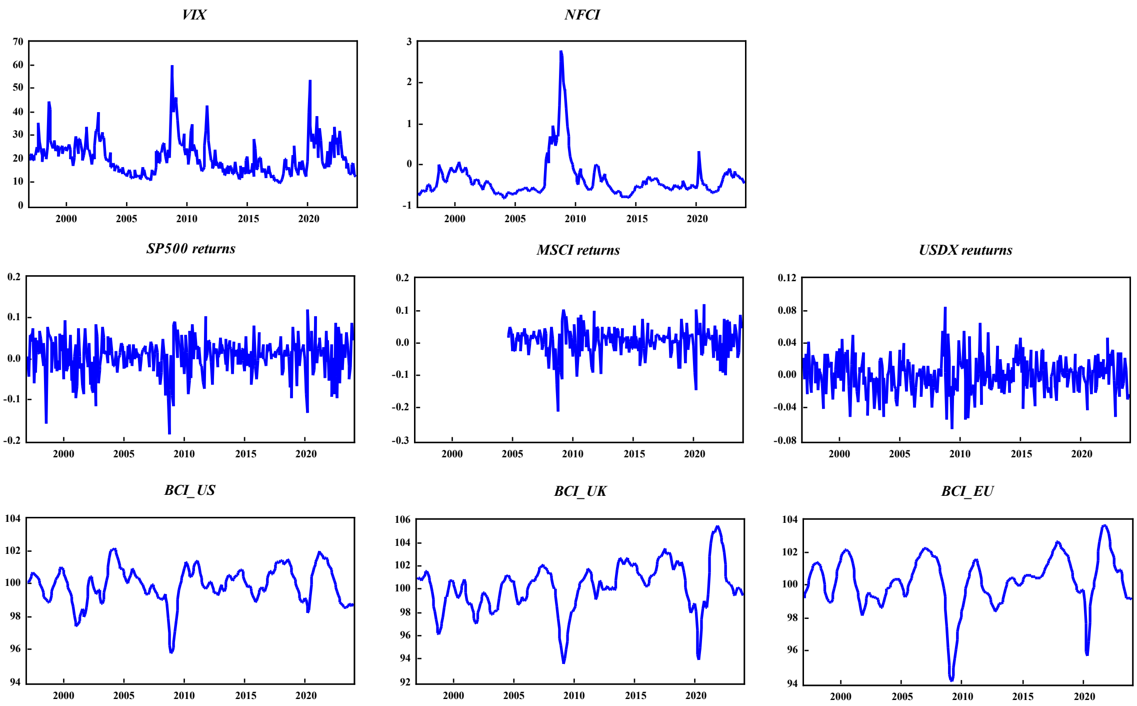
	Monthly data					
	BDI	WTI	GPR	EPU	PPI	US10Y
Mean	2108.123	58.358	101.183	139.798	178.793	3.493
Std. Dev.	1861.573	28.158	51.244	74.352	37.800	1.488
Skewness	2.421	0.232	4.189	1.131	0.329	0.185
Kurtosis	9.574	2.127	29.075	3.671	2.635	2.148
Jarque－Berra	899.812***	13.213***	10126.314***	75.174***	7.627**	11.643***
ADF	－2.648a*	－0.750c	－7.271a***	－4.699b***	1.553c	－1.388c
	Monthly returns/changes					
	y_{BDI}	y_{WTI}	y_{GPR}	y_{EPU}	y_{PPI}	y_{US10Y}
Mean	0.001	0.003	0.003	0.004	0.002	－0.002
Std. Dev.	0.248	0.110	0.235	0.175	0.012	0.097
Skewness	－0.462	－0.776	2.289	0.663	－0.756	－0.535
Kurtosis	8.423	13.364	20.472	4.800	6.076	6.950
Jarque－Berra	407.359***	1478.053***	4390.785***	67.253***	158.078***	225.376***
ADF	－17.594c***	－15.795c***	－16.990c***	－13.990c***	－11.324a***	－16.089c***

Note: The sample period of monthly observation runs from Jan. 1997 to Dec. 2023. Significance at the 1, 5 and 10 % level is denoted by asterisks ***, **, *, respectively. The ADF test uses three different types of constraints: with trend term, with trend term and intercept and with none of them are indicated by a, b, and c next to the estimated value. Jarque–Bera statistics and ADF tests are followed as $\chi 2$ distribution.

4-2. Monthly data of additional samples

In order to verify what are the determinants of variation in the dynamic conditional correlation estimated by the empirical analysis, it is necessary to use additional sample data. Thus, this section provides an explanation of the additional sample and basic statistics, etc. Three groups of candidate determinants of variation are presented in Section 3. The VIX and the NFCI are additional samples in ① Risk Indices group. The VIX is a fear gauge for financial markets published by the CBOE, while the NFCI represents the financial condition index, which is published by the Federal Reserve Bank of Chicago and measures overall financial market stress and accessibility of funding. The second group, ② Financial markets, consists of the 10-year U.S. Treasury yield, as well as the SP500 and the Dollar Index, which are representative indices, and the MSCI All-Country World Equity Index[11], the other four in total. The last group, ③ Economic Trends is an additional sample of business sentiment indices for the U.S. U.K., and Europe, the countries associated with WTI and BDI. These data were obtained from FRED. See Figure 4 and Table 3 for market trends and basic statistics for the additional sample within the sample period, respectively.

Figure 4. Time-series of additional samples monthly data and returns/ changes (1997 ~ 2023)



[11] Note that due to data availability, the MSCI's monthly data start in August 2004.

Table 3. Distributional properties of additional samples and results of stationarity test

	Additional Samples (Monthly data, Monthly returns/changes)							
	VIX	NFCI	y_{SP500}	y_{MSCI}	y_{USDX}	BCI_{US}	BCI_{UK}	BCI_{EU}
Mean	20.632	-0.360	0.006	0.005	0.0002	99.949	100.224	100.245
Std. Dev.	7.908	0.500	0.046	0.046	0.022	1.107	2.073	1.601
Skewness	1.538	3.490	-0.719	-0.886	0.108	-0.719	-0.408	-0.916
Kurtosis	6.622	18.223	4.128	5.219	3.489	4.273	3.947	5.143
Jarque－Berra	304.749***	3786.260***	44.939***	77.937***	3.847	49.782***	21.085***	107.290***
ADF	-6.009a***	-2.952a**	-17.614a***	-13.970c***	-17.334c***	-4.567a***	-6.122b***	-4.904a***

Note: The sample period of monthly observation runs from Jan. 1997 to Dec. 2023. Significance at the 1, 5 and 10 % level is denoted by asterisks ***, **, *, respectively. The ADF test uses three different types of constraints: with trend term, with trend term and intercept and with none of them are indicated by a, b, and c next to the estimated value. Jarque–Bera statistics and ADF tests are followed as $\chi 2$ distribution.

5. Empirical Results

Section 5 discusses step-by-step the estimation results from the empirical model derived in Section 3. It first presents the results of the estimation equations for each monthly returns and then describes the estimation results using the diagonal-BEKK model. Lastly, determinants factors of fluctuations on the dynamic conditional correlation will be discussed with additional analysis.

5-1. Estimated results with diagonal-BEKK modeling

The correlation results for each monthly return dynamics estimated using equations (3) and (6) are shown in Table 4. From Table 4, it is clear that WTI monthly returns at time t have a statistically significant positive correlation with GPR monthly changes at time t-1 and a statistically significant negative correlation with US10Y monthly returns at time t-1. On the other hand, the estimation results reveal that BDI monthly returns at time t have a statistically significant positive correlation with WTI returns at time t-1 and a statistically significant positive correlation with PPI monthly changes at time t-1.

Table 4. Estimated results of monthly retune dynamics on WTI and BDI markets

Model Coefficients	Sample periods: Jan. 1997 ~ Dec. 2023	
	Equation (3)	Equation (6)
ω_1	0.006	—
$y_{GPR.t-1}$	0.034**	—
$y_{EPU.t-1}$	－0.044	—
$y_{US10v.t-1}$	0.117**	—
ω_2	—	－0.001
$y_{WTI.t-1}$	—	0.236***
$y_{PPI.t-1}$	—	2.212**

Notes: The estimated WTI and BDI market monthly returns are represented by equation (3): $y_{WTI,t} = \omega_1 + \alpha y_{GPR,t-1} + \beta y_{EPU,t-1} + \theta y_{US10Y,t-1} + \varepsilon_1$ and (6): $y_{BDI,t} = \omega_2 + \gamma y_{WTI,t-1} + \delta y_{PPI,t-1} + \varepsilon_2$. The sample period of monthly observation runs from Jan. 1997 to Dec. 2023. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively.

While it was expected that GPR and WTI would be correlated based on previous studies, the lack of correlation with EPU monthly changes was unexpected. However, the positive correlation between US10Y monthly returns and WTI monthly returns is as hypothesized, a result that suggests that WTI monthly returns increase when interest rates rise. Combined with the relationship between the economy and interest rates, this means that the monthly return on WTI rises as the economy improves. In other words, when the economy is booming or inflationary, the demand for crude oil for production increases because the economy is more active. It can be inferred from the supply-demand relationship that crude oil prices will rise due to increased demand in the crude oil market, and investors are likely to increase their investments in order to earn more profit. Hence, the correlation suggests that the behavior of investors may eventually lead to higher monthly returns in the crude oil market.

In contrast, the correlation between BDI monthly returns confirms our intuition about the real economy, and it is easy to imagine that as economic conditions become more active, market prices in the shipping market will increase due to supply and demand, and the shipping index will also tend to rise. In addition, from the viewpoint of fuel costs for vessels, it can be considered as an estimation result suggesting that if the crude oil market rises, the cost of vessels will also increase, and the index will rise as a result of the transfer of the cost to wages.

Next, the results of the estimation of the multivariate GARCH model using the error terms estimated from each monthly return dynamics are discussed. The estimation results obtained by the Diagonal-BEKK model in equation (7) are shown in Table 5. It is clear from Table 5 that the coefficient vector A of the error term at time t-1 and the coefficient vector B of H, also called GARCH volatility, are both significant at the 1% level of significance. Thus, the empirical results suggest that it is possible to estimate the covariance of the WTI monthly returns and BDI monthly returns at each time point and to calculate the dynamic conditional correlation, which is a one of target of this paper.

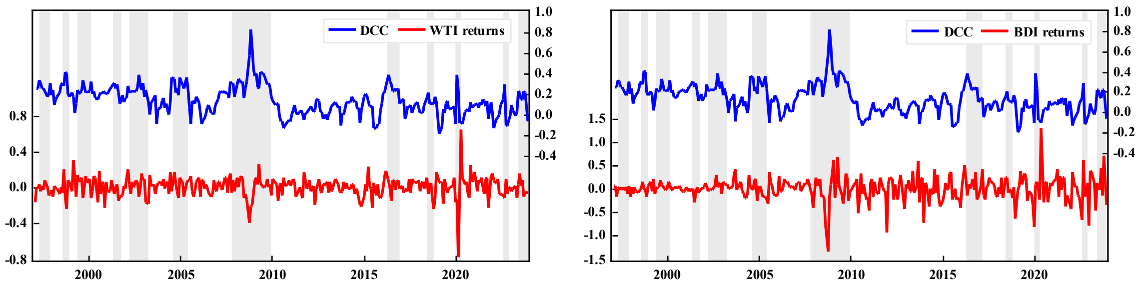
Table 5. Estimated results of variance equation with diagonal-BEKK modeling

Variance Equation Coefficients	Sample periods: Jan. 1997 ~ Dec. 2023 Equation (7)
c_{11}	0.0001*
c_{12}	0.0004*
c_{22}	0.002**
a_{11}	0.193***
a_{22}	0.590***
b_{11}	0.985***
b_{22}	0.733***

Note: The estimated diagonal-BEKK model is represented by equation (7): $H_t = C + A(\varepsilon_{t-1}\varepsilon'_{t-1})A' + B(H_{t-1})B'$. The sample period of monthly observation runs from Jan. 1997 to Dec. 2023. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively.

Using the covariance obtained from equation (7), the dynamic conditional correlation can be estimated from equation (9), and plotted in time-series order in Figure 5. Figure 5 shows that the dynamic conditional correlation fluctuates irregularly, and that the correlation tends to be higher when the respective monthly returns fall. it is note that the gray shading in Figure 5 highlights periods when the estimated dynamic conditional correlations between WTI monthly returns and BDI monthly returns were above 0.2 or when the correlations rose sharply. For example, Figure 5 shows that the correlation is high for shocks with different attributes, such as the global financial crisis triggered by the U.S. bond market and the global economic stagnation caused by the Covid-19 pandemic. On the other hand, the frequent fluctuations in other periods also make it difficult to determine whether geopolitical or financial shock are the cause of these changes. Therefore, in order to solve this problem, the next section will examine the estimated determinants factors of DCC fluctuations in more detail.

Figure 5. Time-series of estimated DCC (1997 ~ 2023)



5-2. Estimated results about determinants factors of fluctuation on DCC

Summary of the results of the analysis of the determinants factors of changes in the dynamic conditional correlations using the three groups (①Risk indices ②Financial markets ③Economic trends) is shown in Table 6 as follows.

First, from the risk indices group, it is clear that DCC is negatively correlated with the EPU at time t and positively correlated with the VIX and NFCI at time t. In terms of price dynamics, one would expect GPR to be correlated, but the results show that it is not. Thus, with regard to the dynamic conditional correlation, the results suggest that it is not related to geopolitical risk but to uncertainty risk associated with policies and risks related to financial markets. Next, from the financial markets group, the results show that DCC is negatively correlated only with the SP500 returns at time t, but not with exchange rates, government bond yields, or global equities. In other words, the results suggest that, limited to financial markets, only the returns of representative U.S. equity indices are among the determinants of fluctuations. The economic trends group also showed a negative correlation only with the U.S. business sentiment index, and no correlation with the U.K. or monthly changes in the producer price index, which are closely related to the Baltic Shipping Index.

Given the results of these analyses, it cannot be stated that markets that are correlated within price dynamics are similarly correlated in the dynamic correlation among market returns, but rather suggest that external markets that did not enter into price dynamics are more determinants of volatility. In addition, Table 6 suggests that factors associated with risk and the U.S. economy tend to be the determinants of volatility.

Table 6. Estimated results of determinants factors on DCC from three aspects

Determinant Factors	Sample periods: Jan. 1997 ~ Dec. 2023		
	Equation (10)	Equation (11)	Equation (12)
GPR_t	0.123e-04	—	—
EPU_t	−0.001***	—	—
VIX_t	0.002**	—	—
$NFCI_t$	0.123***	—	—
$y_{SP500.t}$	—	−2.064*	—
$y_{US10Y.t}$	—	−0.114	—
$y_{USDX.t}$	—	0.402	—
$y_{MSCI.t}$	—	1.490	—
$BCI_{US.t}$	—	—	−0.034***
$BCI_{UK.t}$	—	—	−0.008
$BCI_{EU.t}$	—	—	−0.004
$y_{PPI.t}$	—	—	0.155

Notes: The estimated determinant factors on dynamic conditional correlation between WTI returns and BDI returns are represented by equation (10): $DCC_t = \lambda_0 + \lambda_1 GPR_t + \lambda_2 EPU_t + \lambda_3 VIX_t + \lambda_4 NFCI_t$, (11): $DCC_t = \phi_0 + \phi_1 y_{SP500,t} + \phi_2 y_{US10Y,t} + \phi_3 y_{USDX,t} + \phi_4 y_{MSCI,t}$ and (12): $DCC_t = \psi_0 + \psi_1 BCI_{US,t} + \psi_2 BCI_{UK,t} + \psi_3 BCI_{EU,t} + \psi_4 y_{PPI,t}$. The sample period of monthly observation runs from Jan. 1997 to Dec. 2023. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively.

5-3. Estimated results about determinants factors of fluctuation on DCC with complex case

In Section 5-2, the determinants of fluctuation were estimated for each group, and it became clear that the risk indices tended to be correlated. Based on this result, this section clarifies through an empirical analysis using Equation (13) what the result would be in a complex case.

Table 7 below summarizes the results of the principal component analysis for each group. In Table 7, "PC" refers to the principal components, with PC1 representing the first principal component. The "Proportion" represents the ratio of each PC to the total variance. Finally, "Variables (Loading)" indicates the loading of each variable on each principal component. Note that the shaded areas in Table 7 have been processed to emphasize that they are variables with high loadings in the first and second principal components, respectively.

See first at the risk index group, it is seemed that the sum of the first and second principal components accounted for 70% of the total variance, with VIX being the most highly loaded variable in the first principal component and GPR being the most highly loaded in the second principal component. Next, in the financial markets group, the sum of the first and second principal components exceeded 86% of the total variance; the MSCI monthly return and the US10Y monthly return were the highest loading variables in the first and second principal components, respectively. Finally, in the business climate group, the results also show that the sum of the first and second principal components exceeded 83% of the total variance. The monthly change in the BCI UK was shown to be the most highly loaded variable in the first principal component, while the monthly change in the PPI was the most highly loaded variable in the second principal component. Based on the above results, an empirical analysis will be attempted by substituting the variables that were highly loaded in the first and second principal components into equation (13).

Table 7. The results of Component Principal Analysis

Risk Indices	Proportion	Variables (Loading)			
		GPR_t	EPU_t	VIX_t	$NFCI_t$
PC1	0.419721	-0.05763	0.220068	0.693177	0.683927
PC2	0.28203	0.750615	0.634493	0.038806	-0.18025
PC3	0.212836	0.643094	-0.73716	0.169431	0.11966
PC4	0.085413	0.140306	0.074726	-0.6995	0.696733
Financial Markets		$y_{sp500.t}$	$y_{US10Y.t}$	$y_{USDX.t}$	$y_{MSCI.t}$
PC1	0.599671	0.610959	0.133803	-0.45888	0.631073
PC2	0.261325	0.06393	0.919408	0.387283	0.024782
PC3	0.134574	0.414261	-0.36938	0.792304	0.25338
PC4	0.004429	-0.67159	-0.0186	0.108134	0.732755
Economic Trend		$BCI_{US.t}$	$BCI_{UK.t}$	$BCI_{EU.t}$	$y_{PPI.t}$
PC1	0.627473	0.513492	0.568126	0.555912	0.323297
PC2	0.217595	0.113673	-0.31916	-0.29786	0.892468
PC3	0.115129	-0.83839	0.178756	0.412405	0.308348
PC4	0.039802	0.143226	-0.73717	0.657393	-0.06246

Note: The shaded areas in Table 7 have been processed to emphasize that they are variables with high loadings in the first and second principal components, respectively.

Table 8 below presents the empirical results for the determinants of fluctuations in DCC considering the complex cases estimated by equation (13). PC1 in the table refers to the case in which the variable with the highest loading in the first principal component of each group is the explanatory variable in equation (13), while PC2 refers to the case in which the variable with the highest loading in the second principal component is the explanatory variable in equation (13). The asterisks in the table indicate the significance level of the p-values: *** indicates the 1% level, ** indicates the 5% level, and * indicates the 10% level.

Table 8. The additional results of determinants factors on DCC

Variables	Coefficients
PC1	
VIX_t	0.002
$y_{MSCI.t}$	−0.426*
$BCI_{UK.t}$	−0.016***
PC2	
GPR_t	−0.0002
$y_{US10Y.t}$	−0.099
$y_{PPI.t}$	−1.349**

Notes: The estimated determinant factors on dynamic conditional correlation between WTI returns and BDI returns are represented by equation (13): $DCC_t = \zeta_0 + \zeta_1 PC1_{risk\ indices,t} + \zeta_2 PC1_{financial\ market,t} + \zeta_3 PC1_{economic\ trends,t}$
The sample period of monthly observation runs from Jan. 1997 to Dec. 2023. Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively.

Table 8 suggests that in PC1, or the first principal component, financial markets and business cycle trends are negative determinants of fluctuations with respect to DCC. For PC2, the results suggest that only business climate is a determinant of DCC and negatively related to it. It is very interesting to note that the contrast between the results of Section 5-2, which suggested that the risk index tends to be a determinant of changes in DCC, and the results of PC2, which took into account the multiple cases, is quite striking. In the current social structure, where economic trends or the real economy are not exactly linked to financial markets, it is difficult to determine how a situation in which the real economy and financial markets diverge would affect the determinants of DCC fluctuations. This structure can be seen as one of the reasons for the erratic fluctuations in the DCC.

5-4. Verification of multicollinearity on empirical analysis

Finally, this empirical analysis will examine multicollinearity. This verification process is necessary in order to understand the structure of the determinants of DCC fluctuations again, since there were some discrepancies in the empirical results in Sections 5-2 and 5-4. The simplest method of verification is the Variance Inflation Factor (VIF) test, and the explanatory variables to be verified are those that have statistically significant correlations in this empirical analysis. The final goal is to find a combination of explanatory variables with a VIF value below 10, and to find determinants of DCC fluctuation that can resolve multicollinearity while taking into account complex cases.

Table 9 summarizes the results of several multiple regression analyses in which the VIF values were below 10 and statistically significant. Note that the explained variable in the multiple regression analysis is the DCC. Type A is a multiple regression equation with EPU, monthly returns of SP500, and monthly changes in PPI as explanatory variables. Type B is a multiple regression equation with the monthly changes in GPR, SP500 monthly returns, and PPI as explanatory variables. Type C is a regression equation that incorporates EPU and GPR simultaneously as explanatory variables in light of the results of Type A and Type B. The asterisk marks in the table indicate the significance level, where *** means the 1% level of significance, ** means the 5% level of significance, and * means the 10% level of significance.

It was possible to discover the existence of two types of multiple regression equations, Type A and Type B, suitable for avoiding the multicollinearity problem. This result is different from the results of the group-by-group analysis (Section 5-2) and the analysis using principal component analysis (Section 5-3). The problem of multicollinearity is an unavoidable phenomenon in multiple regression analysis and is a major concern in empirical analysis. Therefore, it is obvious that the more explanatory variables are increased, the higher the frequency of occurrence of multicollinearity. In order to avoid this problem, it was necessary to combine a minimum number of variables, resulting in a compact regression equation, as can be clearly seen in Table 9.

First of all, it should be noted that the results are not consistent with the most highly loaded variable in the first principal component obtained in the principal component analysis. In addition, the results are not entirely consistent with the results for each group, which seems to be a summary of both analyses. An interesting result is that the explanatory variables belong equally to each group (risk indices, financial markets, and business climate), as shown in Table 9: the EPU and GPR belong to the Risk Indices group, the monthly returns of the SP500 to the Financial Markets group, and the monthly changes in the PPI to the Economic Trends group. Unfortunately, the strength or weakness between the variables cannot be discussed in this multiple regression equation, but it can at least be argued that they are equally selected from each group. The fact that one variable from each of these groups constitutes the determinants of change can suggest that the determinants of change in the DCC are all affected by risk, finance, and the economy, and that they are complex. The reason why the direction and causality of the correlation between the crude oil market and the shipping index have not been consistent in previous studies is that the determinants of DCC fluctuations behind both markets are influenced by markets, risks, and the real economy. The questions here are the timing of the fluctuations and the strength-weakness relationship between variables (or groups).

Table 9. Estimated results of multiple regression analysis and Multicollinear test

	Coefficients	VIF
Type-A		
EPU_t	−0.001***	4.584
$y_{sp500.t}$	−0.453***	1.019
$y_{PPI.t}$	−1.714***	1.040
Type-B		
GPR_t	−0.0002*	4.951
$y_{sp500.t}$	−0.489***	1.023
$y_{PPI.t}$	−1.446**	1.034
Type-C		
EPU_t	−0.001***	4.644
GPR_t	−0.0001	5.016
$y_{sp500.t}$	−0.466***	1.024
$y_{PPI.t}$	−1.706***	1.040

Note: Significance at 1, 5 and 10% level is denoted by ***, ** and *, respectively.

As a further addition, Type C is an analysis of what the results would be if the EPU and GPR were combined at the same time. It is interesting to note that the Type C estimation results show a negative and significant result for the EPU, while the GPR is insignificant. When uncertainty and geopolitical risk are considered together, it can be inferred that uncertainty tends to be the factor affecting the DCC of the oil market and the shipping index. However, as the Type B estimation result proves, it is difficult to determine whether there is no correlation at all. Nevertheless, if it is assumed that today's economy is molded by a complex interplay of numerous markets and information, it is preferable to follow the results of Type C.

In summary, this verification shows that, when multicollinearity is taken into account, the determinants of fluctuations in the dynamic correlation between the oil market and shipping indexes are influenced by uncertainty, U.S. stock market returns, or changes in producer prices. On the other hand, the fact that the results are not in complete agreement with those obtained from the principal component analysis and the attribute-by-attribute analysis leads to a discussion of which results should be followed up. Since the base of the analytical method in this paper is multiple regression analysis, it may be important to avoid the problem of multicollinearity. In addition, there are other issues which are the setting of price dynamics. The diagonal-BEKK model employed in this paper can estimate cointegration and dynamic conditional correlation relatively easily among multivariate GARCH models, but it has the disadvantage that convergence of estimation results becomes more difficult as the number of explanatory variables increases. In the empirical model, adding a large number of additional variables often leads to estimation errors, and the final model is constructed as shown in Equations (3) and (6). In other words, it can be pointed out that this may not be the optimal configuration of price dynamics, and it cannot be denied that this may have affected the validation of the determinants of variation. Based on these considerations and the issues highlighted, let us proceed to the conclusion.

6. Conclusions

The purpose of this paper is to estimate the dynamic conditional correlation that exists between the U.S. crude oil market and the Baltic shipping market and to analyze the determinants factors of fluctuations on the estimated dynamic correlation. The diagonal-BEKK model, one of the multivariate GARCH models, is employed to perform the estimation, and the sample period is from January 1997 to December 2023 on a monthly basis. The analysis of the determinants of fluctuation is also conducted using the three perspectives of risk, financial markets, and economic trends. The dynamic conditional correlation between WTI monthly returns and BDI monthly returns is found to be a tendency correlated with risks such as policy-related uncertainty, market returns on U.S. stock market and changes in producer prices.

The evidences that the estimated dynamic conditional correlation between the two markets can be easily influenced by the complex system with risk, finance, and real economy suggests that this may be one of the causes of the complexity of the correlation and causality between the two markets, and this paper is expected to be one of the pieces to solve the mystery of the irregular correlation and causality between the crude oil and shipping markets in many of the previous studies. In addition, while the main task of earlier studies is to estimate dynamic conditional correlations, the attempt in this paper is an empirical result that can also provide new possibilities for those who study the relationship between the crude oil and shipping markets.

As previously discussed in the context of the empirical findings, there are a few areas that require further attention and potential improvement. These include the issue of multicollinearity with multiple regression analysis and the modelling limitations imposed by the diagonal-BEKK model. It is hoped that these issues will be addressed and resolved in future research.

Chapter 3. The Impact of Sentiment Regarding Renewable Energy Investment on the Critical Mineral Market

1. Introduction

The creation of a decarbonized society is a global goal as a solution to the problems of global warming and climate change. As the energy transition and electrification of society progresses in line with these changes in social structure, the importance of the critical minerals market, such as nickel and lithium, is increasing. From an investment perspective, the growth potential of renewable energy is also driving investment in markets for nickel and cobalt, which are essential for battery cathode materials and stability improvements, and copper, which is valued in power grids and precision equipment. In addition, several sentiment indices have been developed to reflect the rise in renewable energy investment, as if to meet the needs of demand.

Under such circumstances, players who are interested in metal markets and investors that place a heavy emphasis on ESG and renewable energy will also be interested in whether the returns of the critical minerals market are due to trends in renewable energy investments or whether it is due to traditional stock market and economic conditions. However, few empirical analyses have focused on a single mineral market, which is becoming increasingly in demand as renewable energy expands. Most of the mainstream research has been on the correlation or spillover between several groupings of metals (e.g., iron ore and aluminum) and another group of commodities (e.g., agricultural crops and fossil fuels). As single minerals, gold and silver are often the main targets of analysis, and analysis limited to ores related to renewable energy, such as nickel and palladium, is very rare in the earlier studies of empirical analysis in finance.

Thus, this paper focuses on the nickel, cobalt and copper market, which are closely related to renewable energy, and examines whether sentiment reflecting higher renewable energy investment is a determinant of increased returns in the nickel, cobalt, and copper market, or whether financial market and economic trends or oil market returns are determinants of increased returns. The empirical analysis will use multiple regression analysis, structural break testing, and state-space models, and will sample monthly data from 2006 to 2023. Candidate for determinants of increasing returns are ①the WilderHill New Energy Global Innovation Index (WH NEX) which is a sentiment index that reflects the rise in renewable energy investment, ②the S&P 500 index (SP500) as a representative of the financial market, ③U.S. Business Confidence Index (BCI US) representing as economic trends, and ④West Texas Intermediate (WTI) crude oil futures, which is treated as a benchmark for the crude oil futures market.

According to the empirical results, first, the estimation results of multiple regression analysis reveals that the monthly returns of WH NEX are positively correlated at statistically significance with the monthly returns of nickel and copper, suggesting that they are the determinants that increase monthly returns. Cobalt, on the other hand, is shown to have a significant positive correlation only for the U.S. business trends. Next, regarding structural break testing, the result reveals that there is a significant structural break only in the copper market, and the estimation result indicates that the structural change occurred in April 2009. Finally, the state-space model analysis supports the results of the multiple regression analysis. It is observed that explanatory variables with significant correlations also changed significantly in response to the sharp fluctuation in the nickel and copper markets. In contrast, the coefficients estimated by the state equation for the cobalt market is observed to fluctuate at similar times as the U.S. business confidence index. In summary, the empirical analysis in this paper indicates that the Renewable Energy Investment Sentiment Index is one of a determinant of increasing monthly returns in the nickel and copper markets, while the monthly returns of cobalt tend to be influenced by the business cycle.

Last of this section, an introduction to the structure of this paper is provided. The next section, Section 2, introduces the renewable energy investment sentiment index and related earlier studies. Section 3 describes the multiple regression analysis model and the state-space model. Section 4 tests the distributional properties of the sample data and the unit root process, and Section 5 discusses the estimation results from the empirical model and the coefficients estimated by the state-space model. Section 6 concludes the paper.

2. Literature Review

As energy conversion and electrification continues to expand, several sentiment indices have been developed in recent years to reflect the rise in renewable energy investment, as if to meet the needs of the market. Sentiment indices are designed to reflect market participants' sentiment about the prospects for future returns. The WilderHill New Energy Global Innovation Index (WH NEX) published by Wilder Hill, which is used in the empirical analysis in this report, is one example of a sentiment index for renewable energy investment. Other indices include the S&P Clean Index (SP Clean) and the S&P Green Index (SP Green) published by S&P Dow Jones Indexes, Inc. While a wide variety of sentiment indices are being developed, there are some important points to note. For example, the SP Green and SP Clean indices are based on the top 100 companies that have a corporate policy of striving to become carbon neutral to reduce CO2 emissions. As such, the index only includes companies that are making efforts to reduce emissions and may include companies that are not involved in renewable energy. WH NEX, on the other hand, is an index of about 80-90 companies that have or are developing innovative technologies focused on clean energy, renewable energy, decarbonization, and efficiency. For these reasons, the WH NEX is used in this empirical analysis.

Next, an introduction to related previous research is presented. With the development of a variety of sentiment indices, analysis of renewable energy investments and related commodity markets is becoming increasingly popular. The number of analyses of commodity markets and financial markets is very small compared to the number of analyses of financial markets. Most of the empirical analyses using the sentiment of renewable energy investment show a research background centered on the transition to a decarbonized society and its contrast with fossil fuels. For example, studies on whether changes in sentiment or returns affect the returns of fossil fuels (see Dias et al., 2023; Tiwari et al., 2023 etc.). These empirical results point to a cointegration or positive correlation between the returns on renewable energy investment sentiment and the returns on fossil fuels. These results suggest that the transition to carbon neutrality could be good for the oil and natural gas markets, which is surprising given the position of fossil fuels in today's decarbonized society. Another study by Dawar et al. (2021) suggests that fluctuations in oil prices can promote sentiment. However, since the sentiment indices used in these previous studies were SP Green and SP Clean, it can be pointed out that the sentiment indices cannot be said to reflect a pure increase in renewable energy investment. In addition, many of the sentiment-indices are based on stock prices and ETFs that reflect the performance of companies. What this means is that it cannot be ruled out that there may be a quasi-positive correlation between the indirect impact of the economy on the fossil fuel market and the sentiment index, which has been elevated. For this reason, there exists a criticism that the correlation between sentiment and fossil fuels is influenced by the economy. But according to a study by Kanamura (2022), the value of renewable energy projects that sell electricity is considered rational because the value of renewable energy projects increases with higher energy prices, suggesting that the economy is not the only factor that causes a positive correlation.

On the other hand, when focusing on the mineral market, a wide range of analytical methods developed in the financial markets have been used, but few have been limited to specific minerals, nickel or cobalt alone. As in Baffes (2007)[12], Sari et al. (2010)[13] or Hernandez et al. (2019)[14] for example, it can be concluded that the analysis between commodities is the mainstream, as studies have been conducted on the correlation and propagation between several groupings of metals (e.g., iron ore and aluminum) and another group of commodities (e.g., agricultural crops and fossil fuels) rather than a single mineral. Although there are cases in which returns structure and correlation analysis is conducted with a single mineral as in the study by Kang et al. (2017), in most cases, precious metals such as gold and silver are the subject of analysis. This seems to be due to the fact that precious metals such as gold and silver are preferred investment targets in portfolio selection with other financial assets, and thus are more likely to be the subject of research. In contrast, nickel and copper have a very strong industrial aspect, which may suggest that their value as investment targets is currently weak. Unfortunately, analysis limited to ores related to renewable energy, such as nickel, cobalt, and palladium, is very rare in the context of empirical analysis in finance.

It is clear from the previous studies mentioned above that studies focusing on three of the critical minerals, nickel and cobalt, which are important for batteries, and the copper market, which is essential for electrification, are very rare. Therefore, examining whether renewable energy investment sentiment plays a role in the returns mechanisms of the three markets can be expected to contribute to recommendations for future investment in metals markets in anticipation

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[12] Commodity-to-commodity analysis was performed at real prices using a deflator index to account for price fluctuations caused by the economy.

[13] An analysis of the co-movement between precious metals, including palladium and gold, and the price of crude oil was conducted.

[14] The relationship between reduced returns in the oil market and reduced returns in precious metals when the oil market is bearish is revealed.

of carbon neutrality and analysis of the critical minerals market. Furthermore, due to recent trends[15], it is economically important to analyze the relationship between the mineral market and the effects of investment in renewable energy and the expansion of electrification. Therefore, this paper will first analyze the relationship between the returns of the nickel, cobalt, and copper markets and renewable energy investment using simple multiple regression analysis, structural break testing, and state-space models. These empirical models will be explained in the next section.

3. Empirical Modeling

This section first provides derivations and an explanation of each equation for the monthly return generating process of the three metal markets which are nickel, cobalt and copper, followed by an explanation of the state-space model.

3-1. Monthly return generating process of nickel, cobalt and copper markets

The nickel, cobalt and copper markets used in the empirical model are defined as follows

$$y_{i,t} = \log\left(\frac{price_{i,t}}{price_{i,t-1}}\right), i = nickel, cobalt, copper \tag{1}$$

where, $price_{i,t}$ indicates monthly prices of each metal markets at time t.

Next, let us describe the explanatory variables that comprise the monthly returns for each market. In this empirical model, a total of four explanatory variables are included, ①the WilderHill New Energy Global Innovation Index which is a sentiment index reflecting the rise in renewable energy investment, ②the S&P 500 Index as a representative of the financial markets, ③Business Confidence Index of U.S. as economic trends of United States, ④West Texas Intermediate crude oil futures which is treated as a benchmark for the crude oil futures market. Thus, these variables will be used as components of the monthly returns on nickel, cobalt and copper markets. In addition, these explanatory variables will likewise be used in the stationary perspective, monthly returns and monthly changes, which will be expressed as follows.

$$X_{j,t} = \log\left(\frac{price_{j,t}}{price_{j,t}}\right), j = WH\ NEX, SP500, BCI\ US, OIL \tag{2}$$

Using equations (1) and (2), the monthly returns on the nickel, cobalt, and copper markets estimated by multiple regression analysis are expressed in equations (3), (4), and (5) below.

$$y_{nickel,t} = c + \beta_{WH\ NEX}X_{WH\ NEX,t} + \beta_{SP500}X_{SP500,t} + \beta_{BCI\ US}X_{BCI\ US,t} + \beta_{OIL}X_{OIL,t} + \varepsilon_t \tag{3}$$

[15] Energy policies of other countries are rapidly changing due to discordant situations and the reelection of a president who is skeptical of climate change issues

$$y_{cobalt,t} = c + \beta_{WH\ NEX}X_{WH\ NEX,t} + \beta_{SP500}X_{SP500,t} + \beta_{BCI\ US}X_{BCI\ US,t} + \beta_{OIL}X_{OIL,t} + \varepsilon_t \quad (4)$$

$$y_{copper,t} = c + \beta_{WH\ NEX}X_{WH\ NEX,t} + \beta_{SP500}X_{SP500,t} + \beta_{BCI\ US}X_{BCI\ US,t} + \beta_{OIL}X_{OIL,t} + \varepsilon_t \quad (5)$$

where, in equation (3) to (5), c indicates constant term of each equation, and ε_t, which represents the error term, is following $\varepsilon_t \sim i.i.d.N(0, \sigma^2)$. $\beta_{j,j=WH\ NEX,SP500,BCI\ US,OIL}$ imply that size of coefficients with explanatory variables against nickel, cobalt or copper's market returns.

3-2. Empirical modeling with State-space modeling

The state-space model can be expressed in terms of two equations, the reference observation equation and the state equation. The observation equation is based on equations (3), (4) and (5) used in multiple regression analysis. The state equation is the state of the coefficients of each explanatory variable in the observation equation.

First, the state-space model of the nickel market can be expressed as follows.

$$\begin{aligned} y_{nickel,t} = c + \tilde{\beta}_{WH\ NEX}X_{WH\ NEX,t} + \tilde{\beta}_{SP500}X_{SP500,t} + \tilde{\beta}_{BCI\ US}X_{BCI\ US,t} \\ + \tilde{\beta}_{OIL}X_{OIL,t} + C_{Kilian}Index_{Kilian,t} + \varepsilon_t \end{aligned} \quad (6)$$

$$\begin{aligned} \tilde{\beta}_{WH\ NEX,t} &= \tilde{\beta}_{WH\ NEX,t-1} + \varepsilon_{WH\ NEX} \\ \tilde{\beta}_{SP500,t} &= \tilde{\beta}_{SP500,t-1} + \varepsilon_{SP500} \\ \tilde{\beta}_{BCI\ US,t} &= \tilde{\beta}_{BCI\ US,t-1} + \varepsilon_{BCI\ US} \\ \tilde{\beta}_{OIL,t} &= \tilde{\beta}_{OIL,t-1} + \varepsilon_{OIL} \end{aligned} \quad (7)$$

where, the observation equation for the monthly returns on the nickel market is expressed in equation (6), while equation (7) refers to the equation of states. In equation (6), the $Index_{Kilian,t}$is index of global real economic activity proposed by Kilian (2009) and this variable will help controlling variables for reduction the effect of China' authority at mineral markets. Also, this variable is denoted as fixed coefficient, it means that $Index_{Kilian,t}$ has not directly affect to state estimation in equation (7).

Likewise, the state-space model of the cobalt and copper markets can be expressed as follows.

$$\begin{aligned} y_{cobalt,t} = c + \tilde{\beta}_{WH\ NEX}X_{WH\ NEX,t} + \tilde{\beta}_{SP500}X_{SP500,t} + \tilde{\beta}_{BCI\ US}X_{BCI\ US,t} \\ + \tilde{\beta}_{OIL}X_{OIL,t} + C_{Kilian}Index_{Kilian,t} + \varepsilon_t \end{aligned} \quad (8)$$

$$\begin{aligned} \tilde{\beta}_{WH\ NEX,t} &= \tilde{\beta}_{WH\ NEX,t-1} + \varepsilon_{WH\ NEX} \\ \tilde{\beta}_{SP500,t} &= \tilde{\beta}_{SP500,t-1} + \varepsilon_{SP500} \\ \tilde{\beta}_{BCI\ US,t} &= \tilde{\beta}_{BCI\ US,t-1} + \varepsilon_{BCI\ US} \\ \tilde{\beta}_{OIL,t} &= \tilde{\beta}_{OIL,t-1} + \varepsilon_{OIL} \end{aligned} \quad (9)$$

where, the observation equation for the monthly returns on the cobalt market is expressed in equation (8), while equation (9) refers to the equation of state. In equation (8), the $Index_{Kilian,t}$is index of global real economic activity proposed by Kilian (2009) and this variable will help controlling variables for reduction the effect of China' authority at mineral markets. Also, this variable is denoted as fixed coefficient, it means that $Index_{Kilian,t}$ has not directly affected state estimation in equation (9).

$$\begin{gathered} y_{copper,t} = c + \tilde{\beta}_{WH\ NEX} X_{WH\ NEX,t} + \tilde{\beta}_{SP500} X_{SP500,t} + \tilde{\beta}_{BCI\ US} X_{BCI\ US,t} \\ + \tilde{\beta}_{OIL} X_{OIL,t} + C_{Kilian} Index_{Kilian,t} + \varepsilon_t \end{gathered} \tag{10}$$

$$\begin{gathered} \tilde{\beta}_{WH\ NEX,t} = \tilde{\beta}_{WH\ NEX,t-1} + \varepsilon_{WH\ NEX} \\ \tilde{\beta}_{SP500,t} = \tilde{\beta}_{SP500,t-1} + \varepsilon_{SP500} \\ \tilde{\beta}_{BCI\ US,t} = \tilde{\beta}_{BCI\ US,t-1} + \varepsilon_{BCI\ US} \\ \tilde{\beta}_{OIL,t} = \tilde{\beta}_{OIL,t-1} + \varepsilon_{OIL} \end{gathered} \tag{11}$$

where, the observation equation for the monthly returns on the copper market is expressed in equation (10), while equation (11) refers to the equation of state. In equation (10), the $Index_{Kilian,t}$is index of global real economic activity proposed by Kilian (2009) and this variable will help controlling variables for reduction the effect of China' authority at mineral markets. Also, this variable is denoted as fixed coefficient, it means that $Index_{Kilian,t}$ has not directly affect to state estimation in equation (11).

It is noted that in the empirical analysis of the state space model, mainly based on the estimation results obtained in the multiple regression analysis, the states equations in equations (7), (9) and (11) will be used to estimate and analyze the trends in the coefficients of variables that have statistically significant correlations.

4. Data Properties

Section 4 describes the distributional characteristics and tests for stationarity for each of the samples in this paper: nickel market, cobalt situation, copper market, WH NEX, SP500, BCI US and OIL.

First, each sample data is monthly data and the sample period is from January 2006 to December 2023[16]. The sample nickel, cobalt, copper, WH NEX, SP500, and OIL are obtained from Investing.com and the Thomson Reuters database. BCI US was obtained from FRED.

Figure 1 plots the monthly data for each sample in a time-series order. Looking at the nickel, cobalt, and copper markets, it can be observed that all markets are characterized by unstable price trends, and that the periods of wild fluctuation are also varied. Compared to the stock and bond markets, the commodity markets are said to be more volatile than the stock and credit markets because they are affected by seasonality and supply-demand relationships, and the nickel, cobalt,

[16] Note that for the cobalt market, the period is January 2010-December 2023 due to data availability.

and copper markets also reflect the unique characteristics of the commodity markets.

However, unlike the gold and platinum markets, which are well-known commodities of the same metal class, it is not possible to determine from Figure 1 whether the market has a financial asset aspect. For this reason, it is highly anticipated what kind of results will be obtained from the empirical analysis conducted in this paper. Next, focusing on the price trends of WH NEX and OIL, the proximity of the periods of turbulent fluctuation suggests that there is a relationship between expectations for renewable energy investment and the crude oil market. In fact, prior studies have indicated a positive correlation, which can be confirmed by the price trend chart. As for the BCI US, it shows some regular changes because it refers to the business cycle, but when compared to the copper market, price fluctuations seem to occur at similar times. Finally, the SP500 is a steadily rising stock market, so it is undeniable that the price changes are time-dependent, but considering the timing of the stock market decline, it is possible that there is a relationship with the nickel market. These are the characteristics of each market that can be seen from the price trends.

Table 1 summarizes the distributional characteristics of the monthly data and monthly returns (or monthly changes) for each sample, as well as the results of testing for the presence of a unit root process. The upper portion of Table 1 represents monthly data, and the lower portion represents monthly returns and monthly changes. The asterisks in the table indicate the significance level: *** means 1%, ** means 5%, and * means 10%. The Augmented Dickey-Fuller test (ADF test) is used to test the unit root process, which is assumed to follow a $\chi 2$ distribution. The Jarque-Bera statistics also follow the $\chi 2$ distribution as in the ADF test.

From Table 1, noting the results of the ADF test on the monthly data, the null hypothesis that the cobalt and copper markets, WH NEX and SP500 have a unit root cannot be rejected. Thus, the test results suggest that if this monthly data were used in the analysis as is, a spurious regression would occur, and proper estimation would not be possible. In contrast, the results for monthly returns and monthly changes are favorable as variables in the empirical model because the null hypothesis can be rejected for all of them.

Figure 1. Time-series of monthly data on five markets and two indices

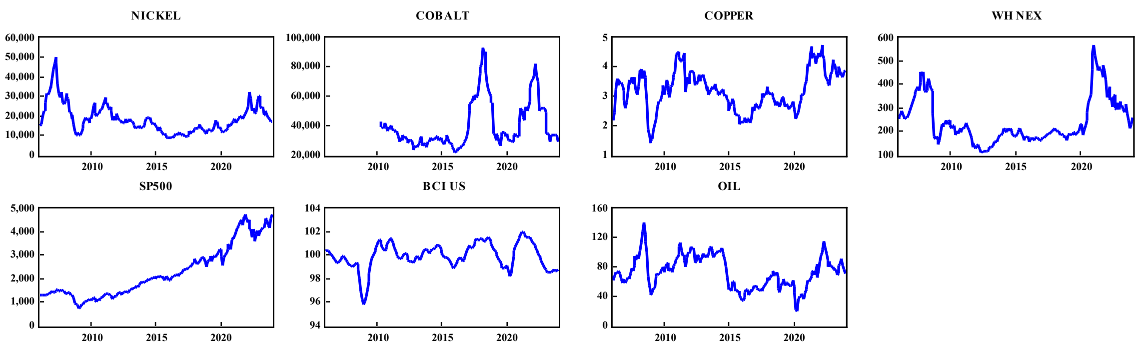

Table 1. Distributional properties of monthly data and returns/changes

	Monthly data						
	Nickel	Cobalt	Copper	WH NEX	SP500	BCI US	OIL
Mean	18342.1	40007.5	3.197	242.09	2252.78	99.95	72.77
Std. Dev.	7511.02	16102.7	0.685	97.529	1097.63	1.115	21.968
Skewness	1.408	1.405	-0.044	1.163	0.771	-0.945	0.178
Kurtosis	5.623	4.168	2.642	3.648	2.406	4.935	2.489
Jarque－Berra	133.290***	63.631***	1.223	52.459***	24.557***	65.872***	3.498
ADF	-2.702*a	-0.884c	-0.034c	-0.702c	2.161c	-5.788***a	-3.055**a
	Monthly returns/changes						
	y_{nickel}	y_{cobalt}	y_{copper}	$X_{WH\ NEX}$	X_{SP500}	$X_{BCI\ US}$	X_{OIL}
Mean	0.001	-0.002	0.003	0.001	0.006	-0.0001	0.001
Std. Dev.	0.1	0.096	0.077	0.084	0.045	0.002	0.116
Skewness	-0.204	-0.868	-0.901	-0.933	-0.774	0.1	-0.949
Kurtosis	3.1	8.048	8.902	6.512	4.477	5.941	15.422
Jarque－Berra	1.586	194.754***	342.670***	142.380***	41.185***	78.228***	1421.277***
ADF	-12.977***c	-11.399***c	-8.043***c	-12.507***c	-13.927***c	-5.780***c	-12.029***c

Note: The sample period of monthly observation runs from Jan. 2006 to Dec. 2023 except cobalt market. The sample period of cobalt market is Jan. 2010 to Dec. 2023. Significance level at the 1, 5 and 10 % is denoted by asterisks ***, **, *, respectively. The ADF test uses three different types of constraints: with trend term, with trend term and intercept and with none of them are indicated by a, b, and c next to the estimated value. Jarque–Bera statistics and ADF tests are followed as $\chi 2$ distribution.

5. Results

Section 5 first discusses the explanation of the estimation results from multiple regression analysis and the test for the presence of structural change. Then, based on the estimation results from the multiple regression analysis and the test for structural change, the estimation results of the state equation analyzed using the state space model are discussed using graphs.

5-1. Estimated results of return generating process on monthly markets

Table 2 summarizes the results of multiple regression analysis using equations (3), (4) and (5), respectively. The values in the table are the estimated results of the coefficients of each explanatory variable. The asterisks in the estimation results indicate the significance level, where *** indicates a 1% level of significance, ** a 5% level of significance, and * a 10% level of significance.

The results of the estimation of the monthly returns of the nickel market will be discussed first. The estimation results show that the monthly returns of the nickel market are positively correlated with the monthly returns of the WH NEX at the 10% level of significance, and positively correlated with the monthly returns of the SP500 at the 10% level of significance. The implication of this result is that the determinants of increasing monthly returns on nickel market are the monthly returns of the WH NEX and the monthly returns of the SP500. In other words, the monthly returns of nickel market increase as the monthly returns of WH NEX increase, and the monthly returns of the nickel market increase as the monthly returns of SP500 market increase. The fact that the nickel market is influenced not only by renewable energy investment sentiment but also by the stock market suggests that the financialization of the commodity market[17] may be beginning to occur in the nickel market as well.

The next, it is discussed the estimation results for the monthly returns of the cobalt market. The estimation results show that the monthly returns of the cobalt market are significantly positively correlated only with the monthly changes in the BCI US. In other words, the results suggest that the returns of the cobalt market utilized in batteries is not related to the sentiment of renewable energy investment but is determined only by changes in the economy. This result is in stark contrast to nickel, which is used in the same battery cathode material, but this difference may be related to political factors in the cobalt market. In fact, cobalt is considered likely to become the fifth conflict mineral. These conflict minerals are those designated by the U.S. Dot Frank Act, established in 2010, which currently covers tin, tungsten, tantalum, and gold. Most of the cobalt is produced in the Republic of Congo, which has been undergoing production activities in violation of ESG in recent years, and is said to have a high possibility of being designated as a new conflict mineral in the future. The market has become unstable due to the extremely high risks involved, and combined with political factors, it is becoming a market that is being shunned not only by battery-related companies but also by investors. On the other hand, cobalt is also used in cutters for processing superalloys, making it an indispensable part of the industrial market. Hence, it can be inferred that the political nature of cobalt as a conflict mineral and its necessity for batteries and industrial use are behind the fact that the returns of the cobalt market is affected only by fluctuations in the business cycle. The results of this empirical analysis can be considered as evidence suggesting that these are involved.

Finally, the results of the estimation of the monthly returns of the copper market are discussed. The estimation results show that the monthly returns of the copper market are significantly positively correlated with the monthly profitability of the WH NEX, business cycle fluctuations, and the monthly profitability of the crude oil market. What this result means is that the return of the copper market increases as demand for renewable energy investments increases, and as the economy fluctuates and the return of the copper market increases as the profitability of the crude oil market increases. This result is consistent with our intuition about copper, which is that copper is an indispensable material not only in industry, but also in lifelines and daily life products. In summary, the estimation results from the multiple regression analysis indicate that the WH NEX monthly return is a determinant of increasing monthly returns in the nickel and copper markets, but not a determinant of increasing monthly returns in the cobalt market.

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[17] see Tang and Xiong (2012) and Silvennoinen and Thorp (2013) etc.

Table 2. Estimated results of multiple regression analysis

	Multiple regression analysis		
	2006M1 ~ 2023M12	2010M4 ~ 2023M12	2006M1 ~ 2023M12
	y_{nickel}	y_{cobalt}	y_{copper}
c	−0.001	0.001	0.002
$X_{WH\ NEX}$	0.201*	−0.033	0.219***
X_{SP500}	0.413*	−0.179	0.233
$X_{BCI\ US}$	4.714	8.553**	7.394***
X_{OIL}	0.071	0.083	0.142***

Notes: The estimated nickel, cobalt and copper market monthly returns are represented by equation (3), (4), and (5). The sample period of monthly observation runs from Jan. 2006 to Dec. 2023 for equation (3) and (5), from Apr. 2010 to Dec. 2023 for equation (4). Significance level at 1, 5 and 10% is denoted by ***, ** and *, respectively.

5-2. Estimated results of Multiple Breakpoint testing

Table 3 summarizes the results for the presence or absence of structural changes in the three metal markets. The Bai-Perron tests of L+1 vs. L sequentially determined breaks method is used to test for structural breaks, and only the copper market is found to have experienced a structural break. The structural break occurred in April 2009. Figure 1 shows that the largest decline in the copper market occurred in December 2008, and that prices began to rise in April 2009. In other words, it can be pointed out that the Lehman Shock may have caused a major change in the copper market. It is also interesting to note that, according to the estimation results of the state space model described below, the sign of one variable that has a significant correlation with the monthly return of the copper market has changed since the structural change date. Section 5-3 provides an analysis and discussion using the state-space model based on the estimation results obtained in this section and Section 5-1.

Table 3. The results of breakpoint testing

	Breakpoint test		
	2006M1 ~ 2023M12	2010M4 ~ 2023M12	2006M1 ~ 2023M12
	y_{nickel}	y_{cobalt}	y_{copper}
Breaks	0	0	1
date			2009M04

Notes: The multiple breakpoint tests based on Bai-Perron tests of L+1 vs. L sequentially determined breaks method.

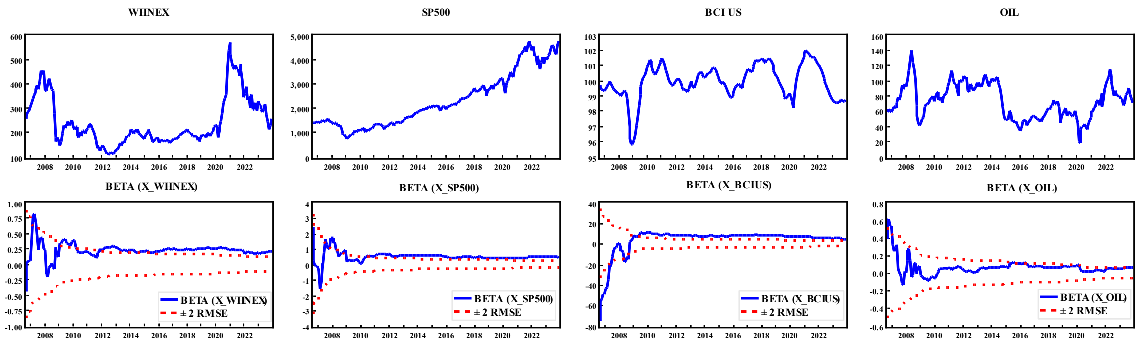
5-3. Estimated state equations by State-space modeling

In this section 5-3, based on the empirical results obtained through the previous empirical analysis, the discussion will be based on the analysis using the three state-space models of the market expressed in equations (6) through (11).

Figure 2 depicts the changes in the state of each explanatory variable from the state-space model of the nickel market expressed in equations (6) and (7), arranged in time-series order. The original monthly data of the explanatory variables are also depicted in Figure 2 to facilitate understanding of the changes in the coefficients of each explanatory variable.

Based on the results of the multiple regression analysis, since the determinants that increase the monthly returns of the nickel market are the monthly profitability of WH NEX and the monthly profitability of the SP500, it will be focused our discussion on these two variables. The lower panel of Figure 2 shows fluctuations of the coefficients of each explanatory variable estimated from the state equation, which at first glance appears to converge to 0. At first glance, however, the coefficients appear to be converging to 0. However, this is only because the change in the state of affairs is markedly large in the period prior to 2010 and thus appears to be a horizontal bar due to the relationship of the figure. As an estimate, it can be observed that the correlation fluctuates around 0.3.

Figure 2. Time-series of monthly data and states of coefficients from equation (7)



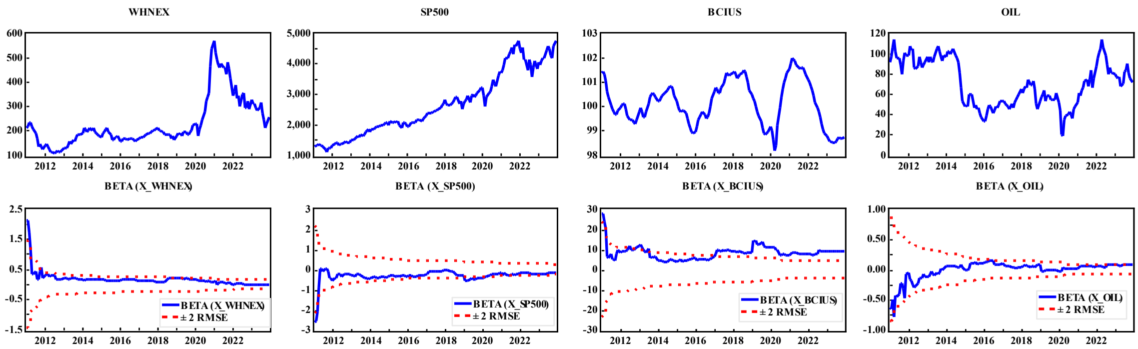
First, as a characteristic point, Figure 2 shows that the coefficient estimated by the equation of state fluctuated significantly around 2006. This can be attributed to the "increase in variables × increase in coefficients" because the nickel market experienced a sharp price increase around 2006 to 2008, and WH NEX and SP500, which have significant correlations, increased as well. This is considered the reason for the extremely large volatility in the market. Behind the price spike of nonferrous metals such as nickel and copper in 2005, which was further exceeded the following year in 2006, it is believed that prices of mineral resources were stimulated by China's resource-based diplomacy, which grew larger due to its economic growth. Although the range of fluctuation in the coefficient has decreased since the price spike in 2006 and the global financial crisis, the correlation still remains around 0.3, making the nickel market a favorable market for players focused on renewable energy investments. In addition, since the market continues to correlate with the stock market, the possibility of financialization can be pointed out, and thus the market is expected to grow more, with the possibility of diverse players participating from the perspective of returns.

Next, Figure 3 depicts the changes in the state of each explanatory variable from the state-space model of the cobalt market expressed in equations (8) and (9), arranged in time-series order.

Figure 3 has the same structure as Figure 2.

Based on the results of the multiple regression analysis, we will focus on the monthly change in the BCI US, since the only determinant that increases the monthly profitability of the cobalt market is the change in the business trends. Compared to the nickel market, it is easy to understand that the coefficients estimated by the state equation fluctuate at similar times as the change in the business confidence index of U.S., as can be observed in Figure 3. but the timing is not the same, and the range of variation in the coefficients is not linked to changes in the business trends, indicating that returns is not necessarily influenced by the business climate. Therefore, the returns of cobalt market tend to be affected by fluctuations in the economy. It will be interesting to see if this relationship will change in the future when cobalt is designated as the fifth conflict mineral. At this point in time, in view of the results of the multiple regression analysis, the market is unattractive for players focused on renewable energy investments because of highly risk markets and low potential to earn return.

Figure 3. Time-series of monthly data and states of coefficients from equation (9)

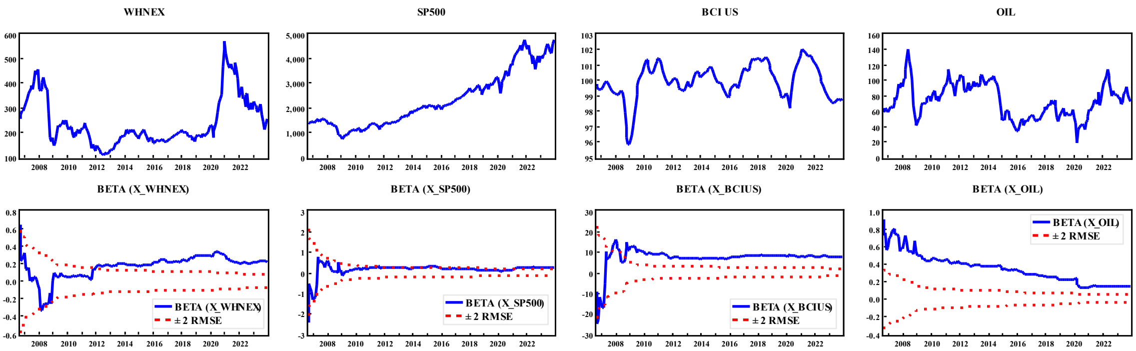


Finally, Figure 4 depicts the changes in the state of each explanatory variable from the state-space model of the cobalt market expressed in equations (10) and (11), arranged in time-series order. Figure 4 also has the same structure as Figure 2.

Based on the results of the multiple regression analysis, the determinants of the increase in the monthly return of the copper market are the monthly returns of WH NEX, the monthly return of SP500, and the monthly return of OIL, so the discussion will focus on these three variables. As with the nickel market, the copper market also has an extreme waveform for the convenience of the graph due to the large change in coefficients before 2010. Therefore, as in the nickel market, the "increase in variables x increase in coefficients" is a factor that has resulted in the range of change shown in Figure 4. Interestingly, WH NEX markets have shifted to a high negative correlation around May 2006, while BCI US market, in contrast, has a high positive correlation. This suggests that the market was not attractive for players focused on renewable energy investments around 2006.

Unlike the other two markets, the copper market has experienced structural break, and it can be pointed out that WH NEX correlation has changed from negative to positive since April 2009, when the market experienced structural break. In light of the results of the multiple regression analysis, it is interesting to note that, in the past, economic fluctuations were the only determinant that increased the returns of the copper market, but since the structural change, renewable energy investments and even the return of the crude oil market have become determinants that have increased the returns of the copper market. It should be noted, however, that it is not clear whether the change in the composition of the determinants is the direct cause of the structural change in the copper market. In summary, the copper market is an attractive market for players focused on renewable energy investments, but it is also a market that is sensitive to the real economy, such as the economy and the crude oil market.

Figure 4. Time-series of monthly data, and states of coefficients from equation (11)



6. Conclusion

This paper attempts to conduct an empirical analysis of the return of the copper market for nickel, cobalt, and copper, the critical minerals that are increasingly in demand as renewable energy expands. The empirical analysis used multiple regression analysis and state-space models to test whether sentiment indices reflecting rising investment in renewable energy, stock market and economic fluctuations, and the crude oil market are determinants of the increasing returns of the nickel, cobalt, and copper markets. Using monthly data from December 2006 to December 2023, the analysis revealed that the monthly return of the copper and nickel markets is positively affected by sentiment reflecting the rise in renewable energy investment. This means that the nickel and copper markets are attractive for players that are heavily invested in renewable energy. In addition, the empirical results suggest that the nickel market has potential for financialization, while the copper market is sensitive to the real economy.

On the other hand, the monthly return of the cobalt market was determined to increase only by fluctuations in the U.S. economy. This may be because cobalt is a high potential to become conflict mineral and is essential for industrial activities, suggesting that the market may remain closed in the future. This empirical evidence suggests that is will be necessary for transition from cobalt market to nickel market for producing battery not only investors but also policy makers due to high risk with geopolitical and finance. It is hoped that the empirical analysis obtained in this paper will assist in the decision-making criteria for investing in critical minerals in light of the global energy situation, which has become increasingly complex in recent years, and the shift toward carbon neutrality and the expansion of electrification.

Note that in adopting the state-space model in this paper, it was necessary to adjust the number of explanatory variables for convergence of the estimation and to set a constraint that the error term in the state equation is not a random walk. Thus, the limited results of this demonstration are a disadvantage. Future research is therefore needed to improve these restrictions and to reconstruct the profitability model.

Conclusion

This paper attempts to discuss the current state of commodity markets by providing an empirical analysis of the price dynamics of commodity markets related to energy resources, including the crude oil market or the mineral market defined as the critical minerals such as nickel and copper, using several classical time series models.

In Chapter 1, focusing on the price dynamics of the U.S. crude oil market, the Markov Regime Switching model was used to analyze how the market changed starting in 2020, when Covid-19 is assumed to have been spread. The results suggest that the dynamics of returns in the U.S. crude oil market are governed by two distinct regimes: one state driven by a negative relationship between returns and implied volatility, and another characterized by a more pronounced negative correlation. It was observed that while the former regime with weak negative correlations predominates in the sample period from 2008 to 2021, regime shifts tend to be more frequent and unstable under more volatile oil price dynamics associated with important events such as the COVID-19 pandemic. Note that the evidence of a negative correlation structure was found to be robust to changes in the estimation period, suggesting that OVX, the crude oil version of the fear index, remains a reliable indicator of market sentiment in the energy market. However, a major challenge in Chapter 1 is the failure to resolve the endogeneity problem in the empirical model. This is due to the fact that OVX is an index calculated from the option prices of ETFs linked to WTI option prices. Hence, a method to resolve the endogeneity constraint in the construction process of the empirical model is required to strengthen the empirical results in this chapter.

In Chapter 2, verifying on crude oil, which has a real demand role in economic activity, the dynamic correlation between the Baltic Shipping Index, a global shipping major, and the U.S. crude oil market was analyzed using a diagonal-BEKK model. The empirical results for the period 1997-2023 showed that the dynamic correlation can be estimated as proved by existing earlier studies even if with price dynamics reflecting geopolitical risks and real economy trends. In addition, when examining the existence of fluctuation determinants behind the complex dynamic correlations, the results showed that not only uncertainty risk but also multiple indices and markets such as U.S. stock indices and business trends were applicable. The dynamic correlation between the crude oil market and the shipping indexes was irregular due to the presence of multiple determinants of change, which may be one of the reasons for the inconsistency in the previous studies. On the other hand, the use of a multivariate GARCH model imposed a major constraint on the construction of price dynamics, which is the issue addressed in this chapter. Even with the BEKK model, it was necessary to limit the number of explanatory variables to some extent from the viewpoint of model specification, and as a result, the empirical results were somewhat conditional. Thus, a more appropriate empirical model needs to be sought in order to deepen the analysis of the determinants of variation.

In Chapter 3, using multiple regression analysis and a state-space model, empirical analysis was applied to determine whether a sentiment index reflecting heightened investment in renewable energy is a determinant factor of increasing returns on the mineral market, which is closely related to the energy sector. Using monthly data from 2006 to 2023, multiple regression analysis reveals that a sentiment index reflecting expectations for renewable energy investment is a determinant of increasing monthly returns in the nickel and copper markets. In contrast, the only determinant of monthly returns in the cobalt market was fluctuations in the U.S. business trend. In addition, the results from the state space model analysis followed the results obtained from the multiple regression analysis. It should be noted that in the copper market, where structural changes were estimated to have occurred, it was observed that the correlation with sentiment turned from negative to positive after the point of structural break. Unfortunately, it was not clear in this chapter what caused the structural change, and this is a topic for future research. It is noted that in the empirical modeling, it was necessary to incorporate the index of Kilian (2009) as a control variable in the estimation equation. This was to improve the accuracy of the estimation due to the large effects of the Chinese economy on the mineral market. However, it cannot be claimed that the model is completely controlled, and room for improvement is one of the issues. In addition, as in Chapter 2, model specification is also an issue for the future.

Commodity markets, including the crude oil market, have grown rapidly since the 2000s and seem to constitute one of the new financial markets. In combination with the fact that they are closely related to real demand, commodity markets are expected to be more complex than the stock market. As the empirical results in Chapters 1 and 2 suggest, the oil market alone is correlated not only with the stock market but also with currency exchange rates and geopolitical risk, and it can be understood as a combination of several factors. On the other hand, as the empirical results show that the crude oil version of the fear index is consistently negatively correlated even when the market becomes more complex, it cannot be assumed that the market is changing into a market that cannot be understood by market participants. Furthermore, the commodity market may reflect not only the real economy, but also financial conditions, geopolitics, and other information, making it a very attractive market for research.

Moreover, what was once invested for risk hedging in portfolios is increasingly focused on investing in the commodity markets themselves. The electrification and energy transitions, as well as other global trends, are expected to lead to more aggressive securing and investing in critical minerals such as nickel and copper. And as suggested in Chapter 3, the nickel market may already be financialized, and even renewable energy investment trends are becoming a factor in boosting profitability. These current conditions suggest that analysis of a wide variety of commodity markets may be the only way to study the future economy more deeply. Hopefully, the empirical research in this paper will help in the process of future commodity analysis.

Finally, it is important to mention the challenges of this paper. Although the empirical results obtained from the chapters are novel with respect to earlier studies, the shortcoming of this paper is that they are all conditional results. This is a problem that suggests that there are limitations in the empirical analysis in constructing more realistic price dynamics. While the endogeneity problem in Chapter 1 and the model specification problems in Chapters 2 and 3 are unavoidable in an empirical analysis, it is believed that these problems can be viewed as advantages that make empirical analysis more attractive. It is also our belief that the many future issues and potential areas for improvement that have been identified through this paper mean that there is that much room for research to be explored. It is hoped that continuing to confront and think about these issues will motivate us to further develop our research on commodity markets.

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