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A Study on Co-movements and Information Spillover Effects Between the International Commodity Futures Markets and the South Korean Stock Markets: Comparison of the COVID-19 and 2008 Financial Crises

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Abstract

Purpose – This paper aims to compare and analyze the co-movements and information spillover effects between the international commodity futures markets and the South Korean stock markets during the COVID-19 and the 2008 financial crises.

Design/methodology – The DCC-GARCH model is used in the co-movements analysis. In contrast, the BEKK-GARCH model is used to evaluate information spillover effects. The statistical data used is from January 1, 2005, to December 31, 2022. It comprises the Korea Composite Stock Price Index data and daily international commodity futures prices of natural gas, West Texas Intermediate crude oil, gold, silver, copper, nickel, soybean, and wheat.

Findings – The results of the co-movement analysis were as follows: First, it was shown that the co-movements between the international commodity futures markets and the South Korean stock markets were temporarily strengthened when the COVID-19 and 2008 financial crises occurred. Second, the South Korean stock markets were shown to have high correlations with the copper, nickel, and crude oil futures markets. The results of the information spillover effects analysis are as follows: First, before the 2008 financial crisis, four commodity futures markets (natural gas, gold, copper, and wheat) were shown to be in two-way leading relationships with the South Korean stock markets. In contrast, seven commodity futures markets, except for the natural gas futures market, were shown to be in two-way leading relationships with the South Korean stock markets after the financial crisis. Second, before the COVID-19 crisis, most international commodity futures markets, excluding natural gas and crude oil future markets, were shown to have led the South Korean stock markets in one direction. Third, it was revealed that after the COVID-19 crisis, the connections between the South Korean stock markets and the international commodity futures markets, except for natural gas, crude oil, and gold, were completely severed.

Originality/value – Useful information for portfolio strategy establishment can be provided to investors through the results of this study. In addition, it is judged that financial policy authorities can utilize the results as data for efficient regulation of the financial market and policy establishment.

Keywords: BEKK-GARCH Model, Co-movement, DCC-GARCH Model, Information Spillover Effect

JEL Classifications: C58, F37

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1. Introduction

Historically, when global emergencies occur, such as foreign exchange or financial crises, there have also been intermittent and simultaneous plunges in financial markets in major countries. This financial market co-movement phenomenon has become an object of interest. It is believed to happen when a country's capital market develops and subsequently opens, increasing the association between individual and global financial market movements. This results in the prices of financial products moving in connection with each other (Choi Kyong-Wook and Cho Dae-Hyoung, 2017).

Since the beginning of 2020, when the COVID-19 pandemic struck globally, this crisis has greatly affected all areas of economic and societal structures (Yoo Jeong-Ho, Park Seul-Ki and Cheong In-Kyo, 2020). The effects of COVID-19 on the domestic macroeconomic and financial fields are reminiscent of the 2008 global financial crisis. Although the fundamental causes of the COVID-19 and 2008 financial crises differ, they greatly impacted the financial markets of developed countries, including South Korea (Nam Young-Jin, Kim Jae-Hyeok, and Jo Ha-Hyun, 2022). The 2008 financial crisis began with the U.S. real estate bubble bursting, leading to the insolvency of the subprime mortgage bonds issued against real estate collateral. This brought about the international financial market crunch. In comparison, the more recent COVID-19 crisis brought about the collapse of the real economy due to the disruption of the global supply chain and the blocking of the movement of goods and people by this global pandemic phenomenon (Kim Hee-Ho and Sun Hao-Feng, 2022).

One inherent research question is how the co-movement and information spillover effects between financial markets changed with the COVID-19 and 2008 financial crises. Thus, this study aims to compare, analyze, and answer intuitive questions about the co-movement and information spillover effects between the international commodity futures markets and South Korean stock markets during the COVID-19 crisis.

Due to the integration of global financial markets and the development of information technology, many investors are increasingly inclined to minimize market risks by constructing a portfolio that includes raw material commodities, such as gold and crude oil, comingled with more traditional assets, such as stocks and bonds. This practice became more prevalent after the global financial crisis. Commodities such as gold and crude oil are typically in high demand by investors as hedging products that can reduce risks during economic downturns. This underscores the importance of understanding the international commodity markets and stock market interrelationships (Lee Sang-Won, 2016).

Existing literature analyzing financial market co-movements generally focuses on the return and volatility spillover effects. The return spillover effects are investigated mainly using cointegration and the error correction model, while the volatility spillover effects are analyzed using the generalized autoregressive conditional heteroskedasticity (GARCH) model. Recent studies have utilized the dynamic conditional correlation (DCC)-GARCH model and Baba, Engle, Kraft, and Kroner(BEKK)-GARCH model (Caporale, Pittia, and Spagnolo, 2022; Karanasos and Kim Jin-Ki, 2005; Cho and Parhizgari, 2008; Lee Ki-Seong and Ryou Jai-Won, 2012; Chittedi, 2015). These econometric models enable the analysis of the co-movement phenomenon and information spillover effects by introducing return and volatility spillover effects into one model.

Overseas studies on the interrelationship between the global commodity futures market and the stock market are being actively conducted. However, research on the relationship between international commodity futures markets and South Korean stock markets is minimal (Jo Ha-Hyun and Kim Jea-Hyeok, 2015; Lee Sang-Won, 2014, 2015, 2016; and Yoon Byung-Jo, 2019). While Yoon Byung-Jo's (2019) work analyzed the tail dependence between multiple futures markets and the Korean stock market, there was no examination of the overall dynamic correlation between the two markets and the volatility spillover effect. Therefore, evaluating the co-movement and information spillover effects between international commodity markets and the South Korean stock markets during the COVID-19 and 2008 financial crises will be a meaningful research contribution.

In this study, we aim to analyze co-movements and information spillover effects between the international commodity futures market and the Korean stock market using the DCC-GARCH model and the BEKK-GARCH model. Co-movement relationships between financial markets are not fixed but have a time-varying characteristic depending on changes in the environment of financial markets. Therefore, this study seeks to dynamically analyze co-movements between the international commodity futures market and the Korean stock market using the DCC-GARCH model, which includes the assumption that the correlation between variables is time-varying. In particular, the DCC-GARCH model can be used to estimate the level of impact at a specific point in the crisis period (2008 financial crisis and corona crisis). Rather than scrutinizing information spillover effects dynamically, the return and volatility spillover effects for a certain period after the occurrence of the global crises should be explored to be able to evaluate the level of mutual influences between financial markets. Thus, this study aims to statically analyze the information spillover effects between the international commodity futures markets and the South Korean stock markets using the BEKK-GARCH model. In particular, through the analysis of the information spillover effects, this study will empirically confirm the leading-delay relationships between the international commodity futures markets and the South Korean stock markets and derive policy implications.

Chapter 1 describes the background of the study and its purpose. Chapter 2 will examine previous studies, while Chapter 3 introduces the study model. Chapter 4 will detail the co-movement analysis between the international commodity futures markets and the South Korean stock markets and the information spillover effects. Lastly, Chapter 5 presents the study results and policy implications.

2. Review of Previous Studies

2.1. Studies on Co-Movements and Information Spillover Effects Between Financial Markets

Studies on the co-movements between financial markets have been actively conducted since stock markets worldwide plummeted in common due to Black Monday in October 1987, when the U.S. stock market crashed.

Early studies on the financial market information spillover between countries mainly used stock index return data to analyze correlations between stock markets. Eun and Shim (1989) studied the information spillover effects between the stock markets of nine countries using the vector autoregressive model (VAR) model, while Becker, Finnerty, and Gupta (1990) analyzed the correlation between the U.S. and Japanese stock markets using a regression model. Koch and Koch (1991) examined the correlations between the stock markets of eight countries using a dynamic simultaneous equations model.

From the beginning of the 1990s, studies analyzing not only the rate of return of the financial market but also the apparent interaction between the volatility levels of the financial markets dominated. For instance, Hamao, Masulis, and Ng (1990) investigated the return and volatility spillover effects among the stock markets of three countries, the U.S., Japan, and the U.K. using a univariate GARCH model. Theodossiou and Lee (1993) also analyzed the preceding using a multivariate GARCH-M model, with the results finding that the U.S. market is a major volatility spillover country. In addition, Susmel and Engle (1994) evaluated the volatility spillover effects between the U.S. and U.K. stock markets using the GARCH-T model.

Thereafter, Engle and Kroner (1995) proposed the BEKK-GARCH model that enables simultaneous analysis of the return and volatility spillover effects between financial markets. The BEKK-GARCH model enables analysis of the return and volatility spillover effects between financial markets using residual variance-covariance matrix information. Related studies include Caporale, Pittia, and Spagnolo (2002), Karanasos and Kim (2005), and Jati and Premaratne (2017).

The VAR, GARCH and BEKK-GARCH models above are modeled by assuming they are time-invariant by fixing time. Thus, our methods have a limitation whereby changes in the correlation between two markets over time cannot be analyzed in detail. As a result, Engle (2002) proposed the DCC-GARCH model after including the realistic assumption that the correlations between variables are time-varying in the model. Subsequently, the DCC-GARCH model has been mainly used to analyze dynamic correlations between financial markets in studies such as Cho and Parhizgari (2008), Lee Ki-Seong and Ryou Jai-Won (2012), Chittedi (2015) and Ahn So-Young and Bae Yeon-Ho (2023).

2.2. Studies on the Relationship Between Commodity Futures Markets and Stock Markets

Increased investment demand for commodity futures has resulted in many overseas studies focusing on the interrelationship between commodity futures markets and stock markets. While most early studies centered on the relationship between a single commodity futures market and a given stock market, studies involving multiple futures markets have been increasing recently.

Studies on the relationship between an individual commodity futures market and varying stock markets are overwhelmingly on the relationship between the crude oil and gold futures markets. They have been conducted in earnest since the 1990s and include Jones and Kaul (1996), Maghyereh (2004), Park and Ratti (2008), and Arouri et al. (2012). Their common concern was measuring the impact of the international crude oil futures market on the stock market activity of various countries using VAR and VAR-GARCH models.

Furthermore, several studies on the relationship between the gold futures market and stock markets have been conducted since the global financial crisis in 2008, as gold is widely viewed as a reliable investment product for stable assets. These include Qudan and Yagil (2012), Miyazaki, Toyoshima, and Hamori (2012), Singh and Nadda (2013), and Arouri, Lahiani, and Nguyen (2015). They primarily use the GARCH, the VAR-GARCH, and the DCC-GARCH models to evaluate relationships between the international gold futures market and some country-specific stock markets.

Studies on the relationships between multiple futures markets and stock market activity have also been conducted over the last decade and include Choi and Hammoudeh (2010), Silvennoinen and Thorp (2013), Delatte and Lopez (2013), Mensi, Hammoudeh, and Kang (2015), Tan Xiao-Fen, Zhang Jun-Xiao, and Zheng Xin-Ru (2017).

Using a DCC-GARCH model, Choi and Hammoudeh (2010) assessed the dynamic correlation between the global commodity futures markets, such as Brent crude oil, West Texas Intermediate (WTI) crude oil, copper, gold, and silver, and the U.S. S&P 500 index. They found that while all commodity futures increased after the Iraq war in 2003, their correlation with the S&P 500 index decreased. In addition, they concluded that while the S&P 500 index responded to both financial and geopolitical crises, commodity futures reacted differently to these occurrences.

Silvennoinen and Thorp (2013) analyzed the correlation between stocks, bonds, and commodities futures (a total of 24 commodities, including grains, food, textiles, metals, and crude oil) using a DSTCC-GARCH model. These researchers found that most correlations were close to zero in the 1990s. Moreover, the integration phenomenon gradually appeared at the beginning of the 2000s and peaked during the 2008 global financial crisis.

Delatte and Lopez (2013) analyzed the tail dependence between the international commodity futures markets (metals, agricultural products, and energy) and a given stock market using the DCC-Copula-GARCH model. They found a tail dependence between the commodity futures markets and the stock market, with the two becoming symmetrical over time. In addition, the synchronization between the two markets gradually strengthened and was found to be strongest during the 2008 global financial crisis.

Mensi, Hammoudeh, and Kang (2015) analyzed the correlations between the international commodity futures markets (such as crude oil, gold, silver, wheat, corn, and rice), the Saudi Arabian stock market, and portfolio risk management using a DCC-fractionally integrated asymmetric power autoregressive conditional heteroskedasticity (FIAPARCH) model. The results indicate that the dynamic correlations between most commodity futures (except the silver futures) and the Saudi Arabian stock market were asymmetric. Moreover, it was confirmed that including commodity futures in the risk management portfolio has a more substantial hedging effect.

Tan Xiao-Fen, Zhang Jun-Xiao, and Zheng Xin-Ru (2017) used a BEKK-GARCH model to analyze the two-way volatility spillover effects between global commodity futures markets (such as oil, natural gas, gold, silver, copper, aluminum, wheat, and corn) and international financial markets (such as the global stock and bond indices, the U.S. exchange rate, and the 10-year U.S. Treasury Bond). They uncovered two-way volatility spillover effects between the global commodity futures and financial markets.

In sharp contrast, very few studies exist on the relationship between international commodity futures and the South Korean stock market. Studies on the relationships between the single commodity futures markets and the South Korean stock market include Jo Ha-Hyun and Kim Jea-Hyeok (2015), Lee Sang-Won (2014), and Lee Sang-Won (2015). They analyzed the relationships between crude oil, gold futures, and the South Korean stock market.

The only two studies examining the relationship between multiple commodity futures markets and the South Korean stock market are Lee Sang-Won (2016) and Yoon Byung-Jo (2019). Lee Sang-Won (2016) assessed the volatility spillover effects between the international raw material markets (gold and crude oil) and the South Korean stock market with a vector error correction model (VECM) and Granger causal analysis. They observed that the volatility of the domestic stock market is impacted by volatility in the crude oil and gold markets. Notably, the influence of the crude oil market volatility was particularly substantial. Using a DCC-Copula-GARCH model, Yoon Byung-Jo (2019) evaluated the tail dependence between the global commodity futures market and the South Korean stock market. Empirically studying the tail dependence between the prices of ten global commodity futures (namely, aluminum, zinc, gas oil, gold, silver, heating oil, lead, natural gas, nickel, and crude oil) and the Korea Composite Stock Price Index (KOSPI), he confirmed that the joint movement between the KOSPI and international commodity futures was strengthened in situations of extreme market confusion designated as global financial crises.

2.3. Differences from Previous Studies

As detailed above, the differences between this study and previous studies include the following: First, prior studies mainly analyzed the relationships between the international commodity futures markets and the South Korean stock markets using methods such as the VECM, as well as the VAR and the DCC-Copula-GARCH models. The VAR model and the VECM mainly enable the analysis of short-term return spillover effects, while the DCC-Copula-GARCH model mainly evaluates the tail dependence. The DCC-GARCH model used in this study enables the analysis of the time-varying co-movement between the international commodity futures markets and the South Korean stock markets. In addition, the BEKK-GARCH model allows simultaneous analysis of the return and volatility spillover effects between the two markets.

Second, preceding studies mainly examined the relationship between the international commodity futures markets and the South Korean stock markets during the 2008 financial crisis. In contrast, this study explores the mutual correlations between the international commodity futures markets and the South Korean stock markets during the COVID-19 and 2008 financial crises.

Third, earlier studies are mainly on the relationships between crude oil and gold futures markets and the South Korean stock markets. Furthermore, Yun Byung-jo's (2019) research analyzes the tail dependence between multiple futures markets and the South Korean stock markets. In comparison, this study aims to investigate the relationship between the two markets more systematically and rigorously by simultaneously analyzing the co-movements and information spillover effects between multiple futures markets and the South Korean stock markets.

3. Study Model and Data Analysis

3.1. Study Model

3.1.1. The DCC-GARCH Model

In the multivariate GARCH model, as the number of variables increases, the number of parameters to be estimated increases rapidly, making estimation quite difficult. to solve this problem, Bollerslev (1990) proposed the CCC-GARCH (Constant Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskedasticity) model. however, the CCC-GARCH model assumed that the conditional correlation coefficient matrix was constant and failed to consider the realistic problem that correlations may change over time (Acatrinei, Gorun and Marcu, 2013).

Engle (2002) assumed that the correlation between time series variables varies over time, leading to the proposal of the DCC-GARCH model. The model obtains the standardized residual of the conditional covariance matrix of time series variables with the GARCH model and then estimates the dynamic conditional correlation coefficient. Thus, the DCC-GARCH model is expressed with the following equations:

$$r_t = \mu_t + \epsilon_t \,,\ \ \epsilon_t|\Omega_{t-1} \sim N(0, H_t) \tag{1}$$

$$H_t = D_t R_t D_t = \left(p_{ij,t}\sqrt{h_{ii,t} h_{jj,t}}\right) \tag{2}$$

$$h_{ii,t} = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \tag{3}$$

$$u_t = \frac{\epsilon_t}{\sqrt{h_{ii,t}}} = D_t^{-1}\epsilon_t \sim iid.N(0, I_N) \tag{4}$$

$$R_t = diag\left(\frac{1}{\sqrt{q_{ii,t}}}, \ldots, \frac{1}{\sqrt{q_{jj,t}}}\right)$$

$$Q_t diag\left(\frac{1}{\sqrt{q_{ii,t}}}, \ldots, \frac{1}{\sqrt{q_{jj,t}}}\right),$$

$$Q_t = \left(q_{ij,t}\right) \tag{5}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \tag{6}$$

$$q_{ij,t} = (1 - \alpha - \beta)\overline{p_{ij}} + \alpha u_{t-1} u'_{t-1} + \beta q_{ij,t-1} \tag{7}$$

$$p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}} \tag{8}$$

$$L_t(\theta, \emptyset) = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}[klong(2\pi) + 2log|D_t| + log|R| + u'_t R_t^{-1} u_t] \tag{9}$$

where r_t is an N×1 return on asset vector and Ω_{t-1} is a set of information up to period t-1. H_t is a conditional covariance matrix, D_t is an N×N diagonal matrix of conditional variance, and R_t is an N×N dynamic conditional correlation coefficient matrix. $h_{ii,t}$ is the conditional variance of individual variables at time point t, u_t is the standardized residual, and I_N is the Nth-order identity matrix. $Q_t = (q_{ij,t})$ is a time-variable covariance matrix of standardized residuals, and $\bar{Q} = E\left[u_t u'\right]$ is an unconditional variance matrix of standardized residuals. The condition that non-negative scalar parameters α and β must be greater than 0, and the value of α+β must be smaller than 1 should be satisfied. α indicates that the greater the intensity of the impact, the greater the variance of the time-variable correlation. β is the time taken for the shock to be dissipated, and α+β indicates the continuity of the correlation. $p_{ij,t}$ represents the dynamic conditional correlation coefficient of the DCC-GARCH model. The DCC-GARCH model is estimated using the maximum likelihood estimation method. The conditional log-likelihood function $L_t(\theta, \emptyset)$ is maximized in a two-step procedure that separates the variability part (θ), which is the sum of the univariate GARCH estimates related to D_t and the correlation coefficient part (∅) related to R_t to estimate the parameters.

3.1.2. The BEKK-GARCH Model

The BEKK-GARCH model proposed by Engle and Kroner (1995) enables the analysis of the information spillover effect between financial time series data using information drawn from the variance-covariance matrix of the residuals. One main advantage of the BEKK-GARCH model is that it can guarantee the positive definite of the covariance matrix in situations with weak constraints. The BEKK-GARCH model has the advantage of being able to simultaneously estimate the return spillover effect and volatility spillover effect.

This study will examine the return and volatility spillover effects of the international commodity futures market on the South Korean stock market using the bivariate BEKK-GARCH (1,1) model. The mean equation of the bivariate BEKK-GARCH (1,1) model is expressed with the following equations:

$$R_{1,t} = c_1 + \sum_{j=1}^{p} \alpha_{11,t-j} R_{1,t-j} + \sum_{j=1}^{p} \alpha_{12,t-j} R_{2,t-j} + \varepsilon_{1,t} \tag{10}$$

$$R_{2,t} = C_2 + \sum_{j=1}^{p} \alpha_{21,t-j} R_{1,t-j} + \sum_{j=1}^{p} \alpha_{22,t-j} R_{2,t-j} + \varepsilon_{2,t} \tag{11}$$

$$\varepsilon_{i,t} | \Omega_{t-1} \sim N(0, H_t)$$

where, $R_{1,t}$ and $R_{2,t}$ are the global commodity futures market rates of return and the Korean stock market, respectively. Thus, C_i and $R_{2,t}$ are the parameters to be estimated, $\varepsilon_{i,t}$ is the market shock in period t, and Ω_{t-1} is the available information set. Therefore, the conditional variance-covariance matrix of the bivariate BEKK-GARCH (1,1) model is given by the following equations:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{12}$$

$$C = \begin{bmatrix} C_{11} & 0 \\ C_{21} & C_{22} \end{bmatrix}, A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \quad B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \tag{13}$$

where, H_t is the (2×2) conditional variance-covariance matrix of in period t, C is the constant coefficient matrix, A is the coefficient of the conditional residual matrix, and B is the coefficient of the conditional covariance matrix. α_{12} and α_{21} are the autoregressive conditional heteroskedasticity (ARCH) term parameters, and b_{12} and b_{21} are the GARCH term parameters. Thus, the return spillover effects and the volatility spillover effects between the two markets can be evaluated with α_{12}, α_{21}, b_{12} and b_{21}.

In addition, solving equations (12) and (13) generates the following simultaneous equations:

$$\begin{aligned} \hbar_{11,t} = C_{11}^2 + C_{21}^2 + \alpha_{11}^2\varepsilon_{1,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2\hbar_{11,t-1} \\ +2b_{11}b_{21}\hbar_{12,t-1} + b_{21}^2\hbar_{22,t-1} \end{aligned} \tag{14}$$

$$\begin{aligned} \hbar_{22,t} = C_{22}^2 + \alpha_{12}^2\varepsilon_{1,t-1}^2 + 2\alpha_{22}\alpha_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2\hbar_{11,t-1} \\ +2b_{22}b_{12}\hbar_{12,t-1} + b_{22}^2\hbar_{22,t-1} \end{aligned} \tag{15}$$

$$\hbar_{12,t} = C_{11} + C_{22} + \alpha_{12}\alpha_{11}\varepsilon_{1,t-1}^2 + (\alpha_{11}\alpha_{22} + \alpha_{12}\alpha_{21})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{21}\alpha_{22}\varepsilon_{2,t-1}^2 \\ +b_{11}b_{12}\hbar_{11,t-1} + (b_{11}b_{22} + b_{12}b_{21})\hbar_{12,t-1} + b_{21}b_{22}\hbar_{22,t-1} \tag{16}$$

The parameters of the BEKK-GARCH model can be estimated using the maximum likelihood estimation method. The conditional likelihood function L(θ)) can be expressed with the equation below, where θ is the vector of estimated parameters, and T is the number of observations:

$$L(\theta) = -Tln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(In|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t) \tag{17}$$

3.2. Data Analysis

3.2.1. Variable Selection and Statistical Data

This study analyzes the South Korean stock market and the international commodity futures market. Therefore, the KOSPI (KSP) was selected as the South Korean stock market variable. Variables related to the international commodity futures market were divided into four fields: energy, precious metals, base metals, and grains.

The U.S. natural gas futures price (NGN) and WTI crude oil futures price (WTI) were selected as the variables representing international energy futures. Natural gas and crude oil are important energy resources and affect corporate liquidity and stock prices (Mensi, Al Rababa'a, Vo and Kang, 2021). Studies by Acaravci, Ozturk and Kandir (2012), Zhang, Chevallier and Guesmi (2017), and Ahmed (2018) found that information spillover effects exist in the long term between natural gas futures and the stock market. Natural gas futures on the New York Mercantile Exchange (NYMEX) are one of the most important natural gas futures contracts in the world and are widely used as a price discovery and hedging tool. Meanwhile, oil price volatility has a significant impact on stock prices through various channels such as production costs, interest rates, and inflation (Fisher, 1930; Williams, 1938). US WTI crude oil futures are used as a reference price to determine international crude oil prices. Therefore, this study intends to use the New York Mercantile Exchange's natural gas futures and WTI crude oil futures as international energy variables.

The U.S. gold futures price (GCN) and the U.S. silver futures price (SIN) were the variables chosen to represent global precious metal futures. Gold and silver are diversified investment products (Skiadopoulos, 2012). Hood and Malik (2013) found that gold acts as a hedge against the S&P 500 index as a kind of haven. Lucey and Li (2015) suggested that silver can also be used as a hedging tool. Mensi, Vo and Kang (2017) revealed that all precious metals have an information spillover effect due to the global financial crisis and recession. The New York Mercantile Exchange is one of the world's largest precious metals futures exchanges and has an advanced trading system and strict supervision and management system. Therefore, to study the relationship between precious metals futures and the Korean stock market, COMEX gold futures and COMEX silver futures of the New York Mercantile Exchange were selected.

The U.S. copper futures price (HGN) and the U.K. nickel futures price (NIL) were selected as the variables representing international base-metal futures. Since base-metals are mainly used in manufacturing production, they affect the stock price volatility of related industries (Saishree and Padhi, 2022). Copper is a raw material product whose price changes depending on economic conditions, and economic activity can be predicted through copper price trends (Sadorsky, 2014). Creti, Joëts and Mignon (2013) found that the correlation between copper and the S&P 500 index has strengthened over time since 2003. The New York Mercantile Exchange's COMEX copper futures are referenced as the reference price that determines the international copper price, and are a product with a lot of international investment. Therefore, this paper selected COMEX copper futures as a variable for base-metals futures. Meanwhile, as the production of electric vehicles has recently increased, nickel, a key material for secondary batteries, is attracting attention. Saishree and Padhi (2022) found that nickel futures on the MCX exchange in India have a return spillover effect on the Indian manufacturing stock index and the NSE infrastructure stock index. The London Metal Exchange (LME) is a trading center for major industrial non-ferrous metals and has absolute pricing power over nickel futures. Therefore, this paper selected LME nickel futures as *another* representative variable in the base-metals futures market.

The U.S. soybean futures price (ZSN) and the U.S. wheat futures price (ZWN) were chosen as the variables representing global grain futures. Currently, the prices of primary products, including agricultural products, are attracting attention as an important factor affecting the stock market (Chang and Fang, 2022). Korea imports soybeans from major soybean exporting countries such as the United States and Brazil (Son Eun-Ae and Lim Song-Soo, 2019). Hu and Xiong (2013) found that U.S. soybean futures affect stock prices in major East Asian countries such as China, Japan, Hong Kong, Korea, and Taiwan. Mensi, Beljid, Boubaker and Managi (2013) found that there was a significant volatility spillover effect between the S&P 500 index and commodity markets (energy, food, gold, and beverages) during the unstable period from 2000 to 2011. In particular, it was revealed that when the stock market is unstable, Mill's hedging effect is the greatest. The Chicago Board of Trade (CBOT) is the world's first agricultural futures market and is currently the world's most representative and largest agricultural commodity exchange. The Chicago Futures Exchange's futures prices for items such as corn, soybeans, and wheat are used as a reference price for price determination in international agricultural trade. Therefore, in order to study the relationship between agricultural product futures and the Korean stock market, Chicago Futures Exchange's CBOT soybean futures and CBOT wheat futures were selected as variables.

The statistical data comprise daily data on individual variables from January 1, 2005, to December 31, 2022, with the number of observed values of time series data totaling 5,138. To analyze the co-movements between the international commodity futures markets and the South Korean stock markets, we divided the study period into the entire period (ALL) from January 1, 2005–December 31, 2022. Furthermore, to analyze the volatility spillover effects, the analysis period was divided into the period before the financial crisis (January 1, 2005–December 31, 2007), the period after the financial crisis (January 1, 2008–December 31, 2010), the period before the COVID-19 crisis (January 1, 2017–December 31, 2019), and the period after the COVID-19 crisis (January 1, 2020–December 31, 2022)[1].

Fig. 1 shows of the daily returns of KOSPI and international commodity futures market. The KOSPI and international commodity futures market were found to be highly volatile during the 2008 financial crisis and 2020 COVID-19 crises.

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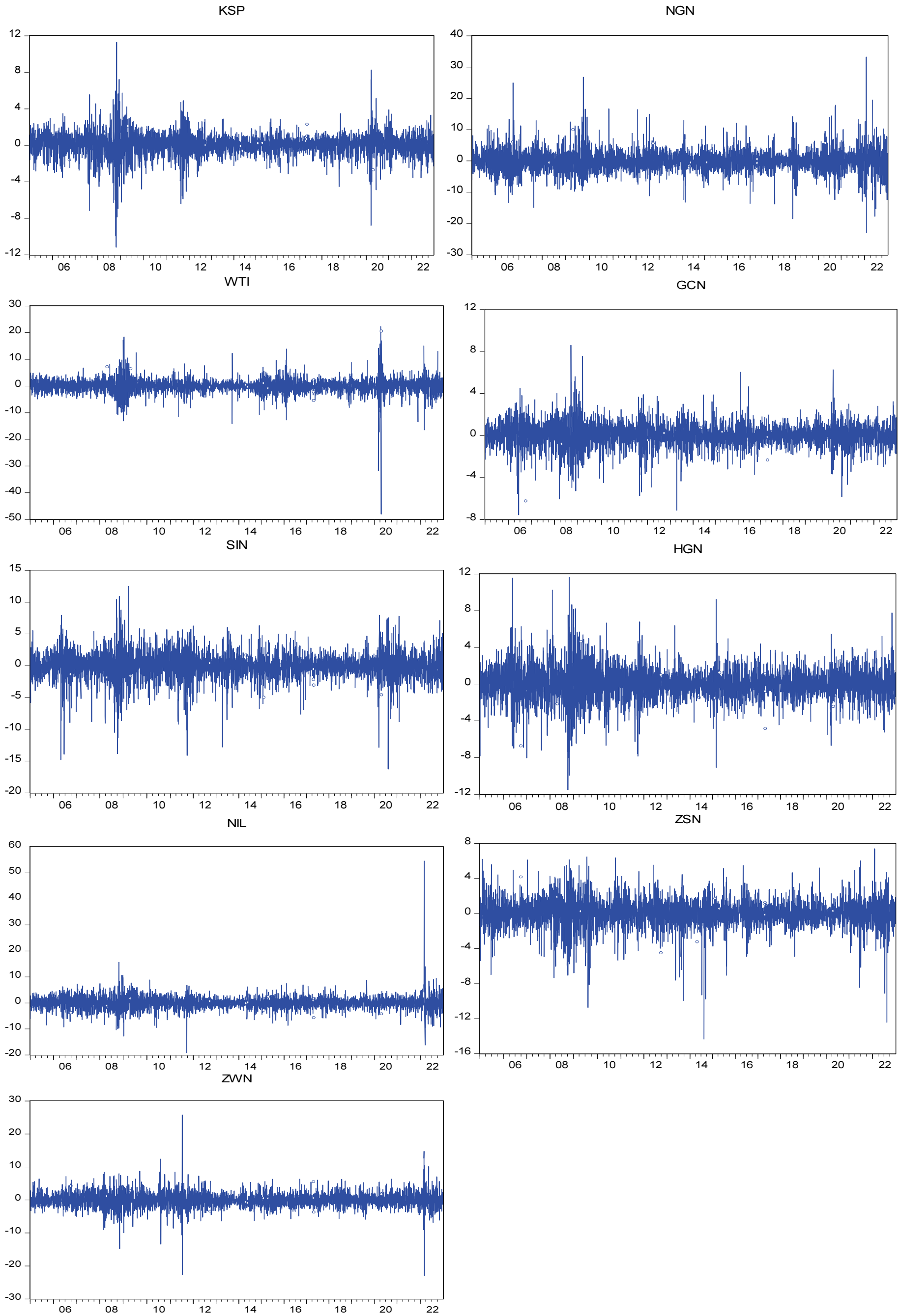
[1] The KOSPI indices data is obtained from the Korea Exchange (KRX), the US commodity futures prices data is from the New York Mercantile Exchange (NYMEX), and the UK nickel futures prices data is from the London Metal Exchange (LME).

Fig. 1. The Daily Return of International Commodity Futures and KOSPI



Notes: The X-axis shows years; The Y-axis shows return (%).
Sources: KRX, NYMEX and LME (2005. 01. 01 – 2022. 12. 31).

3.2.2. Basic Statistics

Table 1 illustrates the basic statistics of the daily return data of the KOSPI and international commodity futures prices[2]. An examination of standard deviations shows that of natural gas futures to be the highest, indicating that the investment risk of natural gas futures is relatively high. The kurtosis was greater than the normal distribution value of 3. At the same time, the Jarque–Bera statistics were significant at the 1% level, indicating that the time series data followed the characteristics of a normal distribution.

Table 1. Basic Statistics on International Commodity Futures and KOSPI Daily Return (1)

Variables	Stage	Minimum value	Maximum value	Average	Standard Deviation	Kurtosis	Jarque-Bera
KSP	ALL	-11.172	11.284	0.021	1.243	11.609	13763.030***
	I	-7.178	5.534	0.101	1.229	5.691	262.860***
	II	-11.172	11.284	0.01	1.77	10.358	1734.299***
	III	-4.541	3.473	0.011	0.78	5.767	289.593***
	IV	-8.767	8.251	0.002	1.38	8.641	976.007***
NGN	ALL	-22.952	33.204	-0.007	3.437	9.426	7788.859***
	I	-14.893	24.959	0.025	3.578	7.299	613.621***
	II	-9.7	26.771	-0.071	3.658	8.525	1114.794***
	III	-18.441	14.151	-0.076	2.751	10.133	1555.012***
	IV	-22.952	33.204	0.1	4.586	8.51	947.467***
WTI	ALL	-48.081	22.295	0.014	2.701	36.504	207269.400***
	I	-4.897	6.75	0.107	1.85	3.023	0.087*
	II	-13.065	18.444	-0.009	3.088	7.568	667.652***
	III	-8.079	9.682	0.019	1.877	5.684	228.029***
	IV	-48.081	22.295	0.033	4.107	36.656	35457.020***
GCN	ALL	-7.558	8.589	0.032	1.127	7.973	4569.886***
	I	-7.558	4.499	0.088	1.194	7.414	695.503***
	II	-6.054	8.589	0.068	1.477	6.503	390.246***
	III	-2.365	2.457	0.037	0.693	3.865	22.566***
	IV	-5.836	6.255	0.025	1.078	6.948	482.116***
SIN	ALL	-16.279	12.469	0.028	2.039	9.487	8106.851***
	I	-14.794	7.937	0.099	2.053	11.296	2376.522***
	II	-13.835	12.469	0.093	2.564	6.689	437.621***
	III	-4.918	4.678	0.014	1.143	4.704	88.600***
	IV	-16.279	7.946	0.04	2.244	9.384	1298.478***

Notes: 1. *p<0.1, **p<0.05, ***p<0.001.
2. ALL Stage: 2005.01.01-2022.12.31; Stage Ⅰ (Financial Crisis Before): 2005.01.01-2007.12.31; Stage Ⅱ(Financial Crisis After): 2008.01.01-2010.12.31; Stage III (COVID-19 Crisis Before): 2017.01.01-2019.12.31; Stage IV (COVID-19 Crisis After): 2020.01.01-2022.12.31.

Sources: KRX, NYMEX and LME (2005.01.01–2022.12.31).

[2] Daily returns are indicated by $R_t = (lnP_t - lnP_{t-1}) * 100$. Among these, (P_t) is the futures price in period t, and (P_{t-1}) is the futures price in period t-1.

Table 1. Basic Statistics on International Commodity Futures and KOSPI Daily Return (2)

Variables	Stage	Minimum value	Maximum value	Average	Standard Deviation	Kurtosis	Jarque-Bera
HGN	ALL	-11.506	11.644	0.022	1.763	7.095	3076.531***
	I	-8.048	11.555	0.101	2.026	5.864	258.867***
	II	-11.506	11.644	0.047	2.509	5.194	150.851***
	III	-4.87	4.399	0.017	1.17	4.524	70.267***
	IV	-6.686	7.765	0.042	1.608	4.408	61.561***
NIL	ALL	-19.198	54.624	0.015	2.428	64.307	693062.700***
	I	-9.271	7.236	0.072	2.332	3.755	29.506***
	II	-12.765	15.635	-0.011	2.977	5.321	169.158***
	III	-5.803	8.719	0.048	1.727	4.963	116.477***
	IV	-16.245	54.624	0.101	3.273	108.617	346077.700***
ZSN	ALL	-14.343	7.397	0.023	1.574	9.285	7726.826***
	I	-6.952	6.208	0.108	1.497	5.224	153.741***
	II	-10.738	6.476	0.017	2.07	5.241	202.517***
	III	-4.878	5.223	-0.009	1.064	5.205	152.524***
	IV	-12.433	7.397	0.065	1.574	11.819	2515.440***
ZWN	ALL	-22.888	25.805	0.021	2.215	14.711	25143.290***
	I	-5.118	7.118	0.142	1.914	3.381	21.969***
	II	-14.759	12.404	-0.016	2.768	5.779	248.256***
	III	-5.872	6.282	0.044	1.757	3.971	40.813***
	IV	-22.888	14.779	0.045	2.419	17.376	6345.201***

Notes: 1. *p<0.1, **p<0.05, ***p<0.001.

2. ALL Stage: 2005.01.01-2022.12.31; Stage Ⅰ (Financial Crisis Before): 2005.01.01-2007.12.31; Stage Ⅱ (Financial Crisis After): 2008.01.01-2010.12.31; Stage III (COVID-19 Crisis Before): 2017.01.01-2019.12.31; Stage IV (COVID-19 Crisis After): 2020.01.01-2022.12.31.

Sources: KRX, NYMEX and LME (2005.01.01–2022.12.31).

3.2.3. The Augmented Dickey–Fuller (ADF) Test

Table 2 illustrates the results of ADF tests of the time series data. The level variables indicated that the time series data were unstable as unit roots at the 5% significance level. Still, the differential variables were identified to be stable time series at the 1% significance level. Therefore, time series analysis can be performed on the daily rate-of-return data from the South Korean stock market and the global commodity futures market.

Table 2. ADF Test Results of Time Series Data

Variables	ADF Test Statistic				
	ALL	**I**	**II**	**III**	**IV**
KSP	-1.734	-0.724	-0.862	-1.633	-1.102
NGN	-2.984	-2.077	-1.007	-2.354	-1.531
WTI	-2.553	-0.892	-1.366	-1.941	-1.240
GCN	-1.196	-0.101	-0.222	-0.919	-3.240
SIN	-2.092	-1.159	0.562	-2.022	-2.118
HGN	-2.098	-1.446	-0.453	-2.453	-1.402
NIL	-2.758	-1.090	-1.505	-1.559	-2.333
ZSN	-2.136	1.821	-1.554	-2.169	-1.334
ZWN	-2.927	0.986	-1.927	-2.645	-1.578
ΔKSP	-65.694***	-26.064***	-27.281***	-16.627***	-16.962***
ΔNGN	-70.473***	-27.169***	-31.691***	-28.781***	-29.029***
ΔWTI	-41.946***	-29.518***	-29.245***	-28.610***	-26.099***
ΔGCN	-65.735***	-28.163***	-26.817***	-28.618***	-25.687***
ΔSIN	-66.644***	-29.044***	-26.408***	-27.883***	-26.596***
ΔHGN	-71.127***	-28.939***	-30.015***	-27.883***	-27.765***
ΔNIL	-64.490***	-26.942***	-26.954***	-26.846***	-24.545***
ΔZSN	-66.624***	-27.280***	-27.035***	-26.606***	-26.830***
ΔZWN	-67.580***	-25.684***	-27.518***	-26.370***	-26.821***

Notes: 1. *p<0.1, **p<0.05, ***p<0.001.
2. ALL Stage: 2005.01.01-2022.12.31; Stage Ⅰ (Financial Crisis Before): 2005.01.01-2007.12.31; Stage Ⅱ (Financial Crisis After): 2008.01.01-2010.12.31; Stage III (COVID-19 Crisis Before): 2017.01.01-2019.12.31; Stage IV (COVID-19 Crisis After): 2020.01.01-2022.12.31.

Sources: KRX, NYMEX and LME (2005.01.01–2022.12.31).

4. Empirical Analysis

In this study, the co-movements between the international commodity futures markets and the South Korean stock markets (KOSPI) will be first analyzed using the DCC-GARCH (1,1) model. Subsequently, the BEKK-GARCH (1,1) model will be applied to analyze the information spillover effects between the international commodity futures markets and the South Korean stock markets.

4.1. Results of Co-Movement Analysis

4.1.1. Parameter Estimation Results

Table 3 illustrates the results of estimation of the parameters of time series data using the DCC (1,1)-GARCH (1,1) model. As shows, both α and β have positive (+) values, and the values of β, which represent the average regression rate of dynamic conditional correlation, are shown to be in a range from 0.782 to 0.994. In addition, it can be seen that the rate of return data of the international commodity futures markets and South Korean stock markets are stable as the condition of $\alpha+\beta<1$ is satisfied. The value of $\alpha+\beta$, which indicates the long-term persistence of the impact, is close to 1, indicating that a volatility clustering phenomenon is appearing.

Table 3. Estimation Results of Parameters Using DCC (1,1)-GARCH (1,1) Model

Variables	α	β	α + β
NGN	0.003	0.929 ***	0.933 ***
	(0.5752)	(0.0000)	
WTI	0.013	0.903 ***	0.917 ***
	(0.1081)	(0.0000)	
GCN	0.004 ***	0.994 ***	0.998 ***
	(0.0045)	(0.0000)	
SIN	0.003	0.987 ***	0.989 ***
	(0.2847)	(0.0000)	
HGN	0.007 **	0.977 ***	0.983 ***
	(0.0460)	(0.0000)	
NIL	0.017 **	0.933 ***	0.949 ***
	(0.0142)	(0.0000)	
ZSN	0.003	0.994 ***	0.996 ***
	(0.1029)	(0.0000)	
ZWN	0.004	0.782 ***	0.786 ***
	(0.6190)	(0.0000)	

Notes: *p<0.1, **p<0.05, ***p<0.001.
Sources: KRX, NYMEX and LME (2005.01.01–2022.12.31).

4.1.2. Co-Movement Analysis Results

The dynamic conditional correlation between the natural gas (NGN) futures market and the KOSPI market is as follows: the NGN-KSP correlation coefficient was found to have fluctuated within the range of -0.036 to 0.059. Before the 2008 financial crisis, the correlation coefficient plummeted to 0.030, but after the financial crisis, it temporarily rose to 0.059. Meanwhile, the correlation coefficient dropped to the 0.020 level before the COVID-19 crisis, then had a temporary rise to 0.048 afterward.

The dynamic conditional correlation between the crude oil (WTI) futures market and the KOSPI market is as follows: the WTI-KSP correlation coefficient was found to have fluctuated within the range of 0.005 to 0.343. Before the 2008 financial crisis, the correlation coefficient declined to the level of 0.050, then rose temporarily to 0.236 after the financial crisis. By comparison, the correlation coefficient dropped to 0.120 before the COVID-19 crisis but temporarily rose to 0.343 post-crisis.

The dynamic conditional correlation between the gold (GCN) futures market and the KOSPI market is as follows: the GCN-KSP correlation coefficient was found to have ranged between -0.141 to 0.188. Before the 2008 financial crisis, the correlation coefficient lowered to the level of 0.020, but afterward, it temporarily rose to 0.065. In contrast, the correlation coefficient fluctuated at the level of 0.030 before the COVID-19 crisis but temporarily rose to 0.188 after the crisis.

The dynamic conditional correlation between the silver (SIN) futures market and the KOSPI market is as follows: the SIN-KSP correlation coefficient was found to have fluctuated within the range of 0.010 to 0.122. Before the 2008 financial crisis, the correlation coefficient fluctuated at the level of 0.030, but after the financial crisis, it temporarily rose to 0.107. In comparison, the correlation coefficient fluctuated at the level of 0.040 before COVID-19 but temporarily rose to 0.122 afterward.

The dynamic conditional correlation between the copper (HGN) futures market and the KOSPI market is as follows: the correlation coefficient of HGN-KSP was found to have fluctuated within the range of 0.115 to 0.339. Before the 2008 financial crisis, the correlation coefficient fluctuated to 0.170, and after the financial crisis, it temporarily climbed to 0.336. In comparison, the correlation coefficient fluctuated at the level of 0.160 before the COVID-19 crisis but temporarily rose to 0.339 afterward.

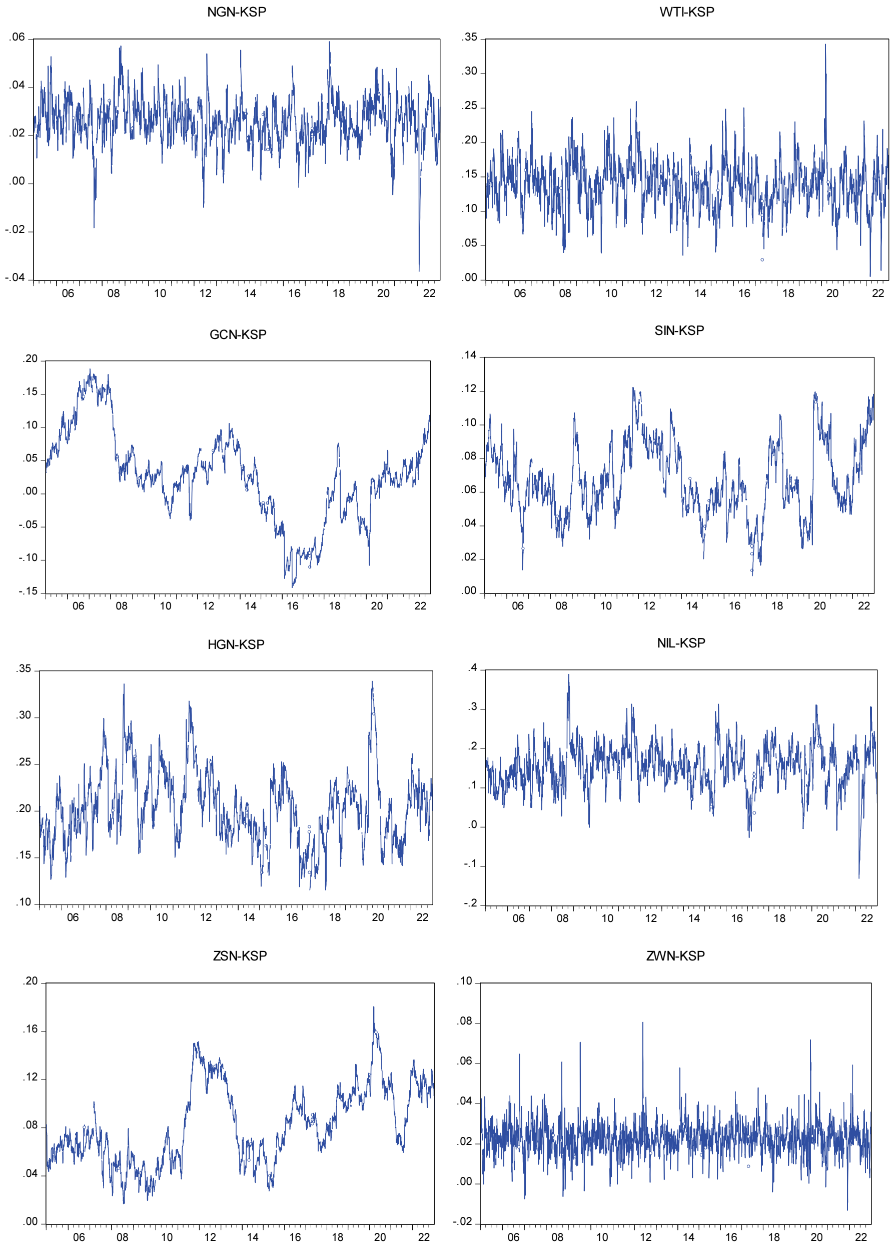
The dynamic conditional correlation between the nickel (NIL) futures market and the KOSPI market is as follows: the NIL-KSP correlation coefficient was found to have fluctuated within the range of -0.131 to 0.389. Before the 2008 financial crisis, the correlation coefficient fluctuated at the level of 0.100, and after the financial crisis, it temporarily rose to 0.389. To compare, the correlation coefficient fluctuated at the level of 0.090 before the COVID-19 crisis but temporarily rose to 0.312 after.

The dynamic conditional correlation between the soybean futures (ZSN) market and the KOSPI market is as follows: the correlation coefficient of ZSN-KSP was found to have fluctuated within the range of 0.017 to 0.180. Before the 2008 financial crisis, the correlation coefficient fluctuated at the level of 0.020, but after the financial crisis, it temporarily climbed to 0.079. In contrast, the correlation coefficient fluctuated at the level of 0.100 before COVID-19 and temporarily rose to 0.180 after.

The dynamic conditional correlation between the wheat (ZWN) futures market and the KOSPI market is as follows: the correlation coefficient of ZWN-KSP was found to have fluctuated within the range of -0.013 to 0.080. Before the 2008 financial crisis, the correlation coefficient fluctuated at the level of 0.020, but after the financial crisis, it temporarily rose to 0.038. In addition, the correlation coefficient fluctuated at the level of 0.020 level before the COVID-19 crisis but temporarily rose to 0.080 afterward.

These dynamic correlation coefficient observations confirmed that the co-movements between the international commodity futures markets and the Korean KOSPI markets were temporarily strengthened after the COVID-19 and 2008 financial crises. The temporary strengthening of the co-movement phenomenon is interpreted to be a result of the global shock in the financial market. In the case of the 2008 financial crisis, the impact on the financial market was very large because the subprime mortgage bonds in the United States became insolvent, leading to a credit crunch in the international financial markets. It is also inferred that the co-movement between the South Korean stock markets and the international commodity futures markets was temporarily strengthened because the South Korean stock markets were also hit hard, right after the outbreak of the financial crisis. The COVID-19 crisis, which began at the end of 2019, led to a global economic downturn due to the pandemic's effect on the financial markets. After the COVID-19 crisis, as access to the online stock market using securities companies' internet portals became more accessible, the trading volume of stocks and overseas financial products increased rapidly. Kim Hee-Ho and Sun Hao-Feng (2022) pointed out that investors tended to increase investments in stocks to compensate for the state of mental panic due to the COVID-19 crisis with stock trading. Thus, it is interpreted that in the case of the COVID-19 crisis, the co-movement between the international commodity futures markets and the KOSPI market was temporarily strengthened as transactions of domestic and foreign stocks and other financial products increased due to the innovation of internet technology and the uneasy psychological conditions of investors.

Fig. 2. The Dynamic Conditional Correlation Between the South Korean Stock Markets and International Commodity Futures Markets



Notes: The author calculated the figures using the KRX, NYMEX, and LME data.
Sources: KRX, NYMEX and LME (2005.01.01–2022.12.31).

4.1.3. Results from Average Correlations Analysis

Fig. 3 below shows the results from the analysis of the averages of the dynamic conditional correlation coefficients between the international commodity futures markets and the South Korean stock markets.

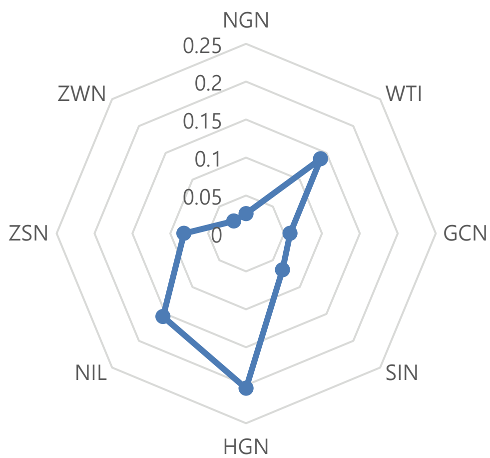
The average correlation coefficients between the base metals, copper (HGN), and nickel (NIL) futures markets and the KOSPI market were relatively large at 0.204 and 0.155, respectively. The high correlations between the KOSPI market and copper and nickel futures markets are interpreted to be attributable to the fact that large manufacturing-related companies listed on the KOSPI market are traditional companies that mainly manufacture semiconductors, automobiles, and ships.

The average correlation coefficient between the crude oil (WTI) futures market and the KOSPI market was 0.139, the third largest value. This is because South Korea, which is strong in the manufacturing industry, relies on imports for crude oil. Hence, fluctuations in international crude oil prices greatly affected companies' production costs.

In addition, the soybean (ZSN) futures market was shown to have the next highest correlation coefficient with the KOSPI market and, in order of precedence, was followed by the silver (SIN), gold (GCN), natural gas (NGN), and wheat (ZWN) futures markets.

The reason why the South Korean stock markets have high correlations with the copper, nickel, and crude oil futures markets is that the country’s industrial structure has a high share of traditional manufacturing and, at the same time, a very high dependence on imports of energy.

Fig. 3. Distribution of Average Correlation Coefficients



Notes: The author calculated the figures using the KRX, NYMEX, and LME data.
Sources: KRX, NYMEX and LME (2005.01.01–2022.12.31).

4.2. Analysis of Information Spillover Effects

While the DCC-GARCH model enables the analysis of co-movement, that is, the dynamic correlation between the international commodity futures markets and the KOSPI market, it does not do the same for evaluating the level of mutual effects between the two markets. In reality, global shocks such as the 2008 financial and COVID-19 crises are not resolved immediately and continue to have effects after the event. These effects have been known to last from 1 to 2 years on the short end to 3 to 5 years at the longest. Therefore, this study aims to analyze the information spillover effects between the international commodity futures markets and the KOSPI market for three years before and after the COVID-19 and 2008 financial crises.

Furthermore, this paper examines the information spillover effects between the international commodity futures markets and the KOSPI market before and after the COVID-19 and 2008 financial crises using the bivariate BEKK-GARCH (1,1) model. Here, $\alpha_{12}(\alpha_{21})$ is an ARCH term parameter and represents the effects of new information (2008 financial or COVID-19 crises) in the international commodity futures markets (South Korean stock markets) on the South Korean stock markets (international commodity futures markets). In other words, the return spillover effects and $b_{12}(b_{21})$, a GARCH term parameter, represent the effect of past information (return volatility) on the international commodity futures markets (South Korean stock markets) on the South Korean stock markets (international commodity futures markets)—that is, the volatility spillover effects. In addition, this paper verifies whether there are information spillover effects between the two markets through Wald test[3]. Meanwhile, it is expected that if there is a mutual spillover effect between the two markets, there should be a two-way leading effect, and if one market has a spillover effect on the other market, there should be a one-way leading effect.

4.2.1. Results from the Analysis of Information Spillover Effects Before and After the 2008 Financial Crisis

The information spillover effects between the natural gas futures market (NGN) and the KOSPI market were as follows: Before the financial crisis, α_{12} and b_{12} were 0.029 and -0.005, indicating that both were statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. In addition, α_{21} and b_{21} were -0.329 and 0.125, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that there were two-way return and volatility spillover effects between the natural gas futures market and the KOSPI market. After the financial crisis, both α_{12} and b_{12} were not statistically significant, and the null hypothesis could not be rejected in the Wald test. Moreover, α_{21} was 0.156, indicating that it was statistically significant at the 1% significance level, but b_{21} was not statistically significant, and the null hypothesis was rejected in the Wald test. Thus, it is inferred that although the natural gas futures market did not have an information spillover effect on the KOSPI market, the KOSPI market had a return spillover effect on the natural gas futures market.

The information spillover effects between the crude oil futures market (WTI) and the KOSPI market were as follows: Before the financial crisis, both α_{12} and b_{12} were not

[3] The Wald test proposed by Agresti (1990) is a method to test whether the parameter of an explanatory variable is zero. In this study, the volatility spillover effect between the two markets is reviewed by performing the Wald test on a_{12} and b_{12} for the BEKK-GARCH (1,1) model.

statistically significant, and the null hypothesis could not be rejected in the Wald test, which means that there was no information spillover effect. On the other hand, α_{21} and b_{21} were 0.102 and -0.041, indicating that both were statistically significant at the 10% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that the KOSPI market had one-way return and volatility spillover effects on the crude oil futures market. After the financial crisis, α_{12} and b_{12} were -0.091 and -0.194, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. In addition, α_{21} and b_{21} were -0.647 and 0.645, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that the crude oil futures market and the KOSPI market had return and volatility spillover effects in both directions.

The information spillover effects between the gold futures market (GCN) and the KOSPI market were as follows: Before the financial crisis, α_{12} and b_{12} were -0.153 and 0.186, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Moreover, α_{21} and b_{21} were 0.147 and -0.178, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Hence, it was confirmed that there were return and volatility spillover effects in both directions between the gold futures market and the KOSPI market. After the financial crisis, α_{12} and b_{12} were 0.216 and 0.177, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Furthermore, α_{21} and b_{21} were 0.211 and -0.153, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that there were return and volatility spillover effects in both directions between the gold futures market and the KOSPI market.

The information spillover effects between the silver futures market (SIN) and the KOSPI market were as follows: Before the financial crisis, all of α_{12}, b_{12}, α_{21}, and b_{21} were not statistically significant, and the null hypothesis was not rejected in the Wald test, so it was concluded that there was no information spillover effect between the two markets. After the financial crisis, α_{12} was not statistically significant, but b_{12} was -0.091, indicating that it was statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Meanwhile, α_{21} and b_{21} were -0.315 and 0.237, respectively, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that there were information spillover effects in both directions between the silver futures market and the KOSPI market.

The information spillover effect between the copper futures market (HGN) and the KOSPI market was as follows: Before the financial crisis, α_{12} was not statistically significant, but b_{12} was 0.020, indicating that it was statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. Moreover, α_{21} was 0.156, indicating that it was statistically significant at the 5% significance level, but b_{21} was not statistically significant, and the null hypothesis was rejected in the Wald test. Thus, it was confirmed that there were information spillover effects in both directions between the copper futures market and the KOSPI market. After the financial crisis, α_{12} and b_{12} were 0.181 and -0.242, respectively, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Meanwhile, α_{21} and b_{21} were 0.354 and 0.575, respectively, an indication that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Hence, it was concluded that the copper futures market and the KOSPI market had return and volatility spillover effects in both directions.

The information spillover effects between the nickel futures market (NIL) and the KOSPI market were as follows: Before the financial crisis, both α_{12} and b_{12} were not statistically significant, and the null hypothesis could not be rejected in the Wald test, so it was judged that there was no information spillover effect. Also, α_{21} was 0.148, indicating that it was statistically significant at the 5% significance level, but b_{21} was not statistically significant, and the null hypothesis was rejected in the Wald test. Hence, it is inferred that the KOSPI market had one-way return spillover effects on the nickel futures market. After the financial crisis, α_{12} and were 0.076 and -0.047, respectively, a sign that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Moreover, α_{21} and b_{21} were -0.210 and 0.186, respectively, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Thus, it was confirmed that the nickel futures market and the KOSPI market have return and volatility spillover effects in both directions.

The information spillover effects between the soybean futures market (ZSN) and the KOSPI market were as follows: Before the financial crisis, all of α_{12}, b_{12}, α_{21}, and b_{21} were not statistically insignificant, and the null hypothesis was not rejected in the Wald test, so it is judged that there was no information spillover effect. After the financial crisis, α_{12} and b_{12} were -0.047 and -0.020, respectively, showing that both were statistically significant at the 10% significance level, and the null hypothesis was rejected in the Wald test. Meanwhile, α_{21} was not statistically significant, but b_{21} was 0.033, meaning that it was statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. Consequently, it was confirmed that there were information spillover effects in both directions between the soybean futures market and the KOSPI market.

The information spillover effects between the wheat futures market (ZWN) and the KOSPI market were as follows: Before the financial crisis, α_{12} and b_{12} were 0.083 and -0.059, respectively, indicating that both were statistically significant at the 1% significance level and the null hypothesis was rejected in the Wald test. Furthermore, α_{21} and b_{21} were -0.113 and 0.117, respectively, a sign that both were statistically significant at the 10% significance level, and the null hypothesis was rejected in the Wald test. Thus, it was confirmed that there were return and volatility spillover effects in both directions between the wheat futures market and the KOSPI market. After the financial crisis, α_{12} was not statistically significant, but b_{12} was -0.065, indicating that it was statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. Meanwhile, α_{21} and b_{21} were -0.418 and 0.158, respectively, confirming that both were statistically significant at the 10% significance level, and the null hypothesis was rejected in the Wald test. Hence, it was confirmed that there were information spillover effects in both directions between the wheat futures market and the KOSPI market.

Table 4. Analysis of Information Spillover Effects Before and After the 2008 Financial Crisis (1)

Futures	Spillover Direction	2008 Financial Crisis					
		Before			After		
		non-main diagonal elements			non-main diagonal elements		
		ARCH-type spillover volatility (α_{12}, α_{21})	GARCH-type spillover volatility (b_{12}, b_{21})	Wald statistic	ARCH-type spillover volatility (α_{12}, α_{21})	GARCH-type spillover volatility (b_{12}, b_{21})	Wald statistic
NGN	NGN→KSP	0.029** (0.012)	-0.005* (0.097)	6.330** (0.042)	0.001 (0.950)	-0.000 (0.966)	0.035 (0.983)
	KSP→NGN	-0.329*** (0.001)	0.125*** (0.002)	11.991*** (0.003)	0.156*** (0.004)	-0.020 (0.247)	13.114*** (0.001)
WTI	WTI→KSP	0.027 (0.231)	-0.006 (0.690)	2.171 (0.338)	-0.091*** (0.004)	-0.194*** (0.000)	397.197*** (0.000)
	KSP→WTI	0.102* (0.065)	-0.041** (0.032)	4.610* (0.100)	-0.647*** (0.000)	0.645*** (0.000)	361.026*** (0.000)
GCN	GCN→KSP	-0.153*** (0.000)	0.186*** (0.000)	86.048*** (0.000)	0.216*** (0.000)	0.177*** (0.000)	133.038*** (0.000)
	KSP→GCN	0.147*** (0.000)	-0.178*** (0.000)	107.865*** (0.000)	0.211*** (0.000)	-0.153*** (0.000)	112.700*** (0.000)
SIN	SIN→KSP	-0.019 (0.243)	0.005 (0.232)	1.755 (0.416)	0.047 (0.161)	-0.091*** (0.000)	77.071*** (0.000)
	KSP→SIN	0.040 (0.447)	-0.026 (0.107)	3.946 (0.139)	-0.315 *** (0.000)	0.237*** (0.000)	74.007*** (0.000)

Notes: 1. *P<0.1, **P<0.05, ***P<0.01.
2. Financial Crisis Before: 2005. 01. 01 – 2007. 12. 31; Financial Crisis After: 2008. 01. 01 – 2010. 12. 31.

Sources: KRX, NYMEX and LME (2005.01.01 – 2007. 12. 31; 2008. 01. 01 – 2010. 12. 31).

Table 4. Analysis of Information Spillover Effects Before and After the 2008 Financial Crisis (2)

Futures	Spillover Direction	2008 Financial Crisis: Before, non-main diagonal elements: ARCH-type spillover volatility $(\alpha_{12}, \alpha_{21})$	Before, non-main diagonal elements: GARCH-type spillover volatility (b_{12}, b_{21})	Before: Wald statistic	After, non-main diagonal elements: ARCH-type spillover volatility $(\alpha_{12}, \alpha_{21})$	After, non-main diagonal elements: GARCH-type spillover volatility (b_{12}, b_{21})	After: Wald statistic
HGN	HGN→KSP	0.042 (0.138)	0.020** (0.030)	4.748* (0.093)	0.181*** (0.000)	-0.242*** (0.000)	461.074*** (0.000)
	KSP→HGN	0.156** (0.015)	0.013 (0.578)	25.938*** (0.000)	0.354*** (0.000)	0.575*** (0.000)	332.856*** (0.000)
NIL	NIL→KSP	0.012 (0.566)	0.006 (0.201)	1.757 (0.416)	0.076*** (0.002)	-0.047*** (0.000)	28.796*** (0.000)
	KSP→NIL	0.148** (0.019)	-0.012 (0.601)	10.242*** (0.006)	-0.210*** (0.001)	0.186*** (0.000)	23.112*** (0.000)
ZSN	ZSN→KSP	-0.013 (0.678)	0.009 (0.517)	1.486 (0.476)	-0.047* (0.064)	-0.020** (0.014)	6.065** (0.048)
	KSP→ZSN	-0.010 (0.786)	0.006 (0.593)	0.415 (0.813)	-0.065 (0.147)	0.033** (0.037)	4.683* (0.096)
ZWN	ZWN→KSP	0.083*** (0.003)	-0.059*** (0.000)	17.702*** (0.000)	0.004 (0.826)	-0.065** (0.013)	7.293** (0.026)
	KSP→ZWN	-0.113* (0.099)	0.117*** (0.005)	8.819 ** (0.013)	-0.418 *** (0.001)	0.158* (0.051)	13.495*** (0.001)

Notes: 1. *P<0.1, **P<0.05, ***P<0.01.

2. Financial Crisis Before: 2005. 01. 01 – 2007. 12. 31; Financial Crisis After: 2008. 01. 01 – 2010. 12. 31.

Sources: KRX, NYMEX and LME (2005.01.01 – 2007. 12. 31; 2008. 01. 01 – 2010. 12. 31).

4.2.2. Analysis of Information Spillover Effects Before and After the COVID-19 Crisis

The information spillover effects between the natural gas futures market (NGN) and the KOSPI market were as follows: Before the COVID-19 crisis, α_{12} was not statistically significant, while b_{12} was 0.076, indicating that it was statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Furthermore, α_{21} and b_{21} were -0.222 and 0.812, respectively, meaning that both were statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that there were information spillover effects in both directions between the natural gas futures market and the KOSPI market. After the COVID-19 crisis, α_{12} and b_{12} were 0.040 and -0.019, respectively, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Moreover, α_{21} and b_{21} were -0.246 and 0.185, respectively, confirming that both were statistically significant at the 5% significance level and that the null hypothesis was rejected in the Wald test. Thus, it was concluded that there were return and volatility spillover effects in both directions between the natural gas futures market and the KOSPI market.

The information spillover effects between the crude oil futures market (WTI) and the KOSPI market were as follows: Before the COVID-19 crisis, α_{12} was -0.071, meaning that it was statistically significant at the 1% significance level, but b_{12} was not statistically significant, and the null hypothesis was rejected in the Wald test. Moreover, α_{21} was not statistically significant, but b_{21} was 0.342, proving that it was statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. Thus, it was confirmed that there were information spillover effects in both directions between the crude oil futures market and the KOSPI market. After the COVID-19 crisis, both α_{12} and b_{12} were not statistically significant, while the null hypothesis was not rejected in the Wald test. This observation confirmed that there was no information spillover effect. Furthermore, α_{21} and b_{21} were 0.264 and -0.253, respectively, a sign that both were statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that the KOSPI market had one-way return and volatility spillover effects with the crude oil futures market.

The information spillover effects between the gold futures market (GCN) and the KOSPI market were as follows: Before the COVID-19 crisis, α_{12} and b_{12} were -0.124 and 0.042, respectively, indicating that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Moreover, both α_{21} and b_{21} were not statistically significant, and the null hypothesis could not be rejected in the Wald test. Hence, it was confirmed that the gold futures market had one-way return and volatility spillover effects on the KOSPI market. After the COVID-19 crisis, both α_{12} and b_{12} were not statistically significant, and the null hypothesis could not be rejected in the Wald test. Meanwhile, α_{21} and b_{21} were 0.132 and -0.094, respectively, meaning that both were statistically significant at the 1% significance level, and the null hypothesis was rejected in the Wald test. Thus, it was confirmed that the KOSPI market had one-way return and volatility spillover effects on the gold futures market.

The information spillover effects between the silver futures market (SIN) and the KOSPI market were as follows: Before and after the COVID-19 crisis, all of α_{12}, b_{12}, α_{21}, and b_{21} were not statistically significant, and the null hypothesis could not be rejected in the Wald test. Thus, it is judged that there was no information spillover effect between the silver futures market and the KOSPI market before and after the COVID-19 crisis.

The information spillover effects between the copper futures market (HGN) and the KOSPI market were as follows: Before the COVID-19 crisis, α_{12} and b_{12} were -0.105 and 0.160, respectively, indicating that both were statistically significant at the 10% significance level, and the null hypothesis was rejected in the Wald test. In addition, both α_{21} and b_{21} were not statistically significant, and the null hypothesis could not be rejected in the Wald test. Therefore, it was confirmed that the copper futures market had one-way return spillover effects and volatility spillover effects on the KOSPI market. After the COVID-19 crisis, all of α_{12}, b_{12}, α_{21}, and b_{21} were not statistically significant, and the null hypothesis was not rejected in the Wald test, so it is judged that there is no information spillover effect.

The information spillover effects between the nickel futures market (NIL) and the KOSPI market were as follows: Before the COVID-19 crisis, α_{12} and b_{12} were -0.048 and 0.013, respectively, indicating that both were statistically significant at the 1% significance level and the null hypothesis was rejected in the Wald test. Meanwhile, both α_{21} and b_{21} were not statistically significant, and the null hypothesis could not be rejected in the Wald test. Hence, it was confirmed that the nickel futures market had unidirectional return and volatility spillover effects on the KOSPI market. After the COVID-19 crisis, all of α_{12}, b_{12}, α_{21}, and b_{21} were not statistically insignificant, and the null hypothesis was not rejected in the Wald test, so it is judged that there was no information spillover effect.

The information spillover effect between the soybean futures market (ZSN) and the KOSPI market was as follows: Before the COVID-19 crisis, α_{12} was -0.048, indicating that it was statistically significant at the 10% significance level. However, b_{12} was not statistically significant, and the null hypothesis could not be rejected in the Wald test, so it was judged that there was no volatility spillover effect. Meanwhile, α_{21} and b_{21} were -0.221 and -0.070, respectively, indicating that both were statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. Therefore, it was confirmed that the KOSPI market had one-way return and volatility spillover effects on the soybean futures market. In contrast, after the COVID-19 crisis, all of α_{12}, b_{12}, α_{21}, and b_{21} were not statistically insignificant. At the same time, the null hypothesis was not rejected in the Wald test, so it was judged that there was no information spillover effect.

The information spillover effects between the wheat futures market (ZWN) and the KOSPI market were as follows: Before the COVID-19 crisis, α_{12} was not statistically significant, but b_{12} was -0.009, indicating that it was statistically significant at the 5% significance level, and the null hypothesis was rejected in the Wald test. On the other hand, both α_{21} and b_{21} were not statistically significant, and the null hypothesis could not be rejected in the Wald test. Therefore, it was confirmed that the wheat futures market had a one-way information spillover effect on the KOSPI market. After the COVID-19 crisis, all of α_{12}, b_{12}, α_{21}, and b_{21} were not statistically insignificant, and the null hypothesis was not rejected in the Wald test, so it is judged that there was no information spillover effect.

4.2.3. Comparison and Analysis of Information Spillover Effects Before and After the COVID-19 and 2008 Financial Crises

The results of comparing and analyzing the information spillover effects between the international commodity futures markets and the KOSPI market before and after the COVID-19 and 2008 financial crises are as follows:

Table 5. Analysis of Information Spillover Effects Before and After the COVID-19 Crisis (1)

Futures	Spillover Direction	Corona Crisis					
		Before			After		
		non-main diagonal elements		Wald statistic	non-main diagonal elements		Wald statistic
		ARCH-type spillover volatility (α_{12}, α_{21})	GARCH-type spillover volatility (b_{12}, b_{21})		ARCH-type spillover volatility (α_{12}, α_{21})	GARCH-type spillover volatility (b_{12}, b_{21})	
NGN	NGN→KSP	-0.008 (0.567)	0.076*** (0.000)	25.317*** (0.000)	0.040*** (0.001)	-0.019*** (0.002)	13.322*** (0.001)
	KSP→NGN	-0.222** (0.028)	0.812*** (0.000)	36.665*** (0.000)	-0.246** (0.045)	0.185*** (0.007)	7.552** (0.023)
WTI	WTI→KSP	-0.071*** (0.006)	0.030 (0.137)	7.729** (0.021)	0.003 (0.849)	0.007 (0.349)	2.869 (0.238)
	KSP→WTI	-0.059 (0.630)	0.342** (0.015)	6.860** (0.032)	0.264** (0.024)	-0.253*** (0.002)	9.327*** (0.009)
GCN	GCN→KSP	-0.124*** (0.003)	0.042*** (0.006)	11.540*** (0.003)	0.021 (0.724)	-0.019 (0.723)	0.279 (0.870)
	KSP→GCN	0.028 (0.361)	0.001 (0.951)	1.884 (0.390)	0.132*** (0.002)	-0.094*** (0.001)	12.854*** (0.002)
SIN	SIN→KSP	-0.034 (0.339)	0.033 (0.139)	2.196 (0.334)	0.039 (0.146)	0.001 (0.941)	2.136 (0.344)
	KSP→SIN	0.070 (0.182)	0.006 (0.844)	3.043 (0.218)	0.044 (0.412)	0.031 (0.148)	0.756 (0.685)

Notes: 1. *P<0.1, **P<0.05, ***P<0.01.
2. COVID-19 Crisis Before: 2017. 01. 01 – 2019. 12. 31; COVID-19 Crisis After: 2020. 01. 01 – 2022. 12. 31.

Sources: KRX, NYMEX and LME (2017. 01. 01 – 2019. 12. 31; 2020. 01. 01 – 2022. 12. 31).

Table 5. Analysis of Information Spillover Effects Before and After the COVID-19 Crisis (2)

Futures	Spillover Direction	Corona Crisis					
		Before			After		
		non-main diagonal elements		Wald statistic	non-main diagonal elements		Wald statistic
		ARCH-type spillover volatility (α_{12}, α_{21})	GARCH-type spillover volatility (b_{12}, b_{21})		ARCH-type spillover volatility (α_{12}, α_{21})	GARCH-type spillover volatility (b_{12}, b_{21})	
HGN	HGN→KSP	-0.105*** (0.001)	0.160* (0.095)	13.665*** (0.001)	0.057 (0.371)	0.039 (0.757)	0.873 (0.646)
	KSP→HGN	0.121 (0.290)	0.386 (0.213)	2.818 (0.244)	0.076 (0.373)	0.256 (0.123)	0.911 (0.634)
NIL	NIL→KSP	-0.048*** (0.001)	0.013*** (0.001)	14.451*** (0.001)	0.010 (0.447)	0.001 (0.832)	1.445 (0.486)
	KSP→NIL	0.089 (0.184)	-0.010 (0.557)	2.296 (0.317)	0.066 (0.200)	-0.011 (0.602)	2.950 (0.229)
ZSN	ZSN→KSP	-0.048* (0.095)	0.013 (0.308)	2.805 (0.246)	-0.018 (0.523)	0.010 (0.396)	0.735 (0.692)
	KSP→ZSN	-0.221*** (0.001)	-0.070** (0.048)	10.903*** (0.004)	0.018 (0.570)	-0.008 (0.541)	0.390 (0.823)
ZWN	ZWN→KSP	0.022 (0.120)	-0.009** (0.022)	5.249** (0.073)	0.009 (0.674)	-0.009 (0.398)	0.747 (0.689)
	KSP→ZWN	0.025 (0.778)	0.010 (0.627)	1.195 (0.550)	0.050 (0.431)	-0.039 (0.301)	1.070 (0.586)

Notes: 1. *P<0.1, **P<0.05, ***P<0.01.

2. COVID-19 Crisis Before: 2017. 01. 01 – 2019. 12. 31; COVID-19 Crisis After: 2020. 01. 01 – 2022. 12. 31.

Sources: KRX, NYMEX and LME (2017. 01. 01 – 2019. 12. 31; 2020. 01. 01 – 2022. 12. 31).

First, before the 2008 financial crisis, four commodity futures markets (natural gas, gold, copper, and wheat) were shown to have two-way leading relationships with the KOSPI market. However, after the financial crisis, seven commodity futures markets, excluding the natural gas futures market, showed two-way leading relationships with the KOSPI market. We interpret this as a further strengthening of the information spillover effects between the international commodity futures markets and the South Korean stock markets after the outbreak of the financial crisis. In particular, it was found that the information spillover effects after the financial crisis were mainly expressed by b_{12} (b_{21}), the GARCH term parameter. The findings above can be interpreted to mean that the information spillover effects between the two markets after the financial crisis was further expressed because they were affected more by the volatility spillover effects. In other words, our prior observations can be interpreted as an indication that the shock of the 2008 financial crisis strengthened the information spillover effects between the Korean KOSPI market and the international commodity futures market.

Second, before the COVID-19 crisis, most international commodity futures markets, excluding natural gas and crude oil futures markets, were found to have led the KOSPI market. This could mean that as protectionism spread due to Brexit and the China–United States trade war, the world economy has been gradually shifting toward de-globalization or regionalization. The prior result indicates that against this backdrop, the South Korean stock markets, which the international financial markets have always heavily influenced, are unidirectionally led by the international commodity futures market.

Third, it was found that after the COVID-19 crisis, there was no information spillover effect between most international commodity futures markets except for natural gas, crude oil, and gold futures markets and the KOSPI market. We interpret the preceding result as confirmation of the effects of the COVID-19 pandemic and the breakout of the Russia–Ukraine War. These incidents have led to the price of crucial raw materials soaring, the collapse of global supply chains, such as disruptions in import and export logistics, and obstacles to the free movement of goods and people, leading to the collapse of the real economy. As a result, there was no information spillover effect between the KOSPI market and international commodity futures markets. Meanwhile, the KOSPI market and the natural gas futures market were found to lead in both directions. This is because South Korea has an outsized influence on the international natural gas market due to its substantial global imports of LNG. In addition, the KOSPI market was found to lead the crude oil and gold futures market in one direction, and this is because crude oil and gold futures are derivative financial products in which domestic investors invest heavily.

5. Conclusion

This study analyzed co-movements and information spillover effects between international commodity futures markets and South Korean stock markets using daily return data from January 1, 2005, to December 31, 2022. The DCC-GARCH model was used in the co-movement analysis, and the BEKK-GARCH model was used to analyze information spillover effects.

The results of the co-movement analysis are as follows: First, after the COVID-19 and 2008 financial crises, co-movements between the international commodity futures markets and the South Korean stock markets were temporarily strengthened. This indicates that the international commodity futures markets and South Korean stock markets temporarily move in the same direction when a global shock has occurred.

Second, the South Korean stock markets were shown to have high correlations with the copper, nickel, and crude oil futures markets. This is because the South Korean industrial structure has a high proportion of traditional manufacturing, and at the same time, the dependence on the import of energy is very high.

The results of the analysis of information spillover effects are as follows: First, before the 2008 financial crisis, four commodity futures markets (natural gas, gold, copper, and wheat) were shown to have a two-way leading relationship with the South Korean stock markets. However, after the financial crisis, seven commodity futures markets, excluding natural and gas futures markets, were shown to have two-way forward relationships with the South Korean stock markets. This is interpreted to mean that the KOSPI and the international commodity futures markets are influencing each other as the global financial markets continue to be integrated following the 2008 financial crisis.

Second, before the COVID-19 crisis, most international commodity futures markets, except for natural gas and crude oil futures markets, were found to have led the South Korean stock markets. This is interpreted as confirming the fact that the South Korean stock markets, which the international financial market has heavily influenced for a long time, have come to be moved in one direction by the international commodity futures markets as the world economy has been gradually shifting toward de-globalization due to the recent spread of protectionism.

Third, it was found that after the COVID-19 crisis, the connection between the South Korean stock markets and international commodity futures markets, except for natural gas, crude oil, and gold futures markets, has been completely severed. During this period, due to the COVID-19 pandemic and the outbreak of the Russia–Ukraine War, the prices of critical raw materials soared, the global supply chains collapsed, with disruptions in import and export logistics, and the movement of goods and people has been obstructed, leading to the collapse of the real economy. Therefore, it is interpreted that the South Korean stock markets and the international commodity futures market did not influence each other.

Based on the above study results, the following policy implications are suggested. The co-movements and information spillover effects between the international commodity futures markets and the South Korean stock markets differed depending on the types of global emergencies. The 2008 financial crisis is a typical example of a financial crisis in one country (the United States) that spread into a global financial crisis. After the financial crisis, each country improved its financial system and the globalization of financial markets accelerated, further strengthening the level of integration between the Korean stock market and international commodity futures markets. In contrast, the corona crisis can be seen as an example of the collapse of the real economy, such as the collapse of the global supply chain and blocking of product movement, which promoted instability in the international financial market. After the coronavirus crisis, each country's policy of isolation was maintained for a long period of time, blocking the movement of goods such as raw materials, which is interpreted to have led to a halt in investment in raw materials. This led to a disconnect between the Korean stock market and the international commodity futures market. In this way, compared to the financial crisis, in the case of the COVID-19 crisis, the impact period on the financial market was longer, and the impact level was more substantial. Meanwhile, since the relationships between the commodity futures markets and the stock markets have a financial hedging function, in cases where the connection between the markets is severed in emergencies, such as the COVID-19 pandemic, the investment risk is expected to be quite large. Therefore, domestic countermeasures should be prepared after closely examining the causes of occurrence and the levels of impact according to the types of global emergencies.

This paper analyzed the co-movements and information spillover effects between the international commodity futures markets and the South Korean stock markets. Furthermore, the results seem to provide useful information to investors for portfolio strategy establishment. Moreover, the financial policy authorities can readily apply or utilize the results as data for efficient financial market regulation and policy establishment.

However, this study could not analyze how the effects of the international commodity futures markets on the stock markets may impact various types of business sectors in South Korea. Therefore, future studies should develop a more rigorous model to study the effects of the international commodity futures markets on the stock markets by business type.

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