The impact of oil price on equity sector volatility in Korea[*]

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Abstract

This paper investigates the transmission of volatility and shocks between world oil price and five industry sector indices of the Korean stock market using a bivariate GARCH model. We also analyze the optimal weights and hedge ratio for building optimal portfolios to minimize the exposure to risk from oil price changes. Our empirical results point to the existence of significant shock and volatility spillovers across oil price and sector market indices, but a heterogeneous impact from oil price. For example, the manufacturing industry (MI), construction (CON), and service (SER) sector indices are significantly sensitive to the world crude oil price (WCO). However, both the finance (FIN) and electricity & communication (EC) sector indices are well insulated from oil market volatility changes. In addition, our examination of optimal weights and hedge ratios suggests adding the oil asset into a well-diversified portfolio and hedging the oil price risk effectively. These findings are of practical importance to financial market participants and may be useful in making optimal portfolio allocation decisions and developing cross-market hedging strategies.

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1. Introduction

The recent oil price fluctuations have renewed interest in the impacts of oil price shocks on economic activities (Hamilton, 2003; Cunado and Perez de Garcia, 2005; Cologni and Manera, 2008; Kilian, 2008; Lardic and Mignon, 2008). In particular, understanding the dynamic relationship between oil price variants and stock markets is an ongoing issue in energy finance. According to a basic theory, the value of stock equals the discounted sum of excepted future cash flows. These discounted cash flows reflect economic conditions (e.g., inflation, interest rates, production costs, income, economic growth, and investor and consumer confidence) and macroeconomic events that are likely to be influenced by oil shocks (Jones and Kaul, 1996; Sadorsky, 1999; Park and Ratti, 2008; Apergis and Miller, 2009; Masih, Peters and De Mello, 2011).

In the literature, a large volume of studies have provided an explanation concerning the linkage between oil prices and stock market indices. A majority of these works show the negative impact of oil price shocks on international stock returns (Jones and Kaul, 1996; Sadorsky, 1999; Park and Ratti, 2008; Chiou and Lee, 2009; Narayan and Narayan, 2010; Lee and Chiou, 2011). These studies have suggested that the oil price shocks may lead input prices to increase, driving profits and returns in different countries or industries (or even firms). However, Huang, Masulis and Stoll (1996) found little evidence of a relationship between oil prices and the S&P 500 market index using a VAR model. Surprisingly, there is a positive relationship between the oil price and stock price of oil companies (Sadorsky, 2001; Boyer and Filion, 2007; El-Sharif et al., 2005). This evidence indicates that oil price increases lead to higher stock returns of oil-related firms.

Given the recent uncertainties of oil prices, dynamic volatility spillover between oil and stock markets are of increasing interest to the construction of optimal risky portfolios and hedge ratios in financial risk management. Malik and Hammoudeh (2007) examined the volatility and shock transmission mechanism among US equity, Gulf equity, and global crude oil markets using a multivariate GARCH framework. They found that the volatility of Gulf equity markets is affected by the volatility of oil markets, but only in the case of Saudi Arabia is there evidence of a significant volatility spillover from the equity market to oil markets. Arouri, Lahiani and Nguyen (2011) also examined the volatility transmission between oil and stock markets in the Gulf countries. They reported that the recent crisis period led to an increase in the existence of volatility spillovers between oil and Gulf equity markets.

Several studies have focused on the volatility transmission mechanism between oil prices and industry-specific sector stock prices. Malik and Ewing (2009) focused on the volatility spillover between oil prices and US sector indexes (Financials, Consumer, Health, Industrials, Technology) and found significant evidence of volatility spillover between oil and sector stock markets. This evidence indicated that the volatility spillover is usually attributed to cross-market hedging and changes in common information. Chang, McAleer and Tansuchat (2009) explored the volatility spillovers between crude oil futures and international oil company stocks using various multivariate GARCH models. They suggested little evidence of volatility spillover effects in any part of the return series.

Arouri, Jouini and Nguyen (2011, 2012) examined the extent of volatility transmission, portfolio deigns, and hedging effectiveness in oil and sector stock returns in Europe and the US. They found that there is significant evidence of unidirectional volatility spillover from oil to Europe sector stock returns, but the empirical evidence supports a bidirectional volatility spillover between oil and US sector markets. Sadorsky (2012) analyzed the volatility spillover between oil prices and the stock prices of clean energy companies and technology companies using various multivariate GARCH models. Surprisingly, the empirical findings suggested that the stock prices of clean energy companies have received more impact from technology stock prices than oil prices.

This study contributes to the extant literature by investigating the linkage between oil price and five sector stock indices in Korea. By doing so, we focus on the relationship between world crude oil price and manufacturing industry, finance, electricity & communication, construction, and service sectors using a bivariate GARCH model with the BEKK framework. An assessment of the volatility linkage between oil price volatility and sector price volatility is crucial for making investment decisions, and for policymakers in implementing appropriate policies for controlling the exposure to oil price risk in industry sector stock markets.

The main contribution of this paper is threefold. First, although previous empirical studies have documented the impacts of oil price movements on sector stock returns in developed countries, little attention has been paid to examining the volatility transmission between oil price and industry-specific sector indices in the Korean stock market. This study initially explores the volatility spillovers between oil price and industry sector indices of Korea.

Second, unlike global or country market indices, all the industries may not be equally dependent on the volatility of oil price. Some sector stock prices may be more severely affected by this volatility than others, depending on whether oil and oil-related products are an input or an output for the industry as well as on the indirect effect of oil price on the industry sector market, on the degree of competition and concentration in the industry, and on the capacity of the industry to transfer oil price shocks to its customers. In this sense, the identification of the heterogeneity of oil price impact on sector sensitivities provides useful information for building international portfolio diversification during oil price swings.

Third, this study further examines optimal portfolio designs and hedge ratios using the estimated conditional covariances between oil and sector stock returns. From a portfolio management point of view, accurate estimation of the time-varying covariance matrix is required to build financial and strategic decisions regarding accurate asset pricing, risk management, and portfolio allocation. Our findings from optimal weights and hedge ratios indicate that investors might make appropriate capital budgeting decisions and effectively manage the exposure to oil price risk in the industry sector markets.

The rest of this paper is organized as follows. Section 2 presents the econometric methodology. Section 3 provides descriptive statistics of the sample data. Section 4 discusses the empirical results. Section 5 presents our conclusions.

2. Methodology

Much attention has focused on how news from one market affects the volatility process of another market. In this study, we analyze the volatility spillover effect between the crude oil market and sector stock markets by using a bivariate framework of the BEKK parameterization (Engle and Kroner, 1995). In this model, the variance-covariance matrix of equations depends on the squares and cross products of innovation ε_t, which is derived from the following mean equation:

$$R_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t), \tag{1}$$

where R_t is the 2×1 vector of returns at time t for each market. The 2×1 vector of random errors, ε_t, represents the innovation for each market at time t with its corresponding 2×2 conditional variance-covariance matrix H_t. The market information available at time $t-1$ is represented by Ω_{t-1}.

This bivariate structure thus facilitates the measurement of the effects of innovations in the mean returns of one market on its own lagged returns and those of the lagged returns of the other market. The standard BEKK parameterization for the bivariate GARCH model (1, 1) is written as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \text{ or} \tag{2}$$

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}, \tag{3}$$

where H_t is a 2×2 matrix of conditional variance-covariance at time t, and C is a 2×2 lower triangular matrix with three parameters. A is a 2×2 square matrix of parameters and measures the extent to which conditional variances are correlated to past squared errors. The elements of A capture the effects of shocks or events on volatility (conditional variance). B is a 2×2 squared matrix of parameters and shows the extent to which current levels of conditional variances are related to past conditional variances.

The conditional variance of the bivariate GARCH (1, 1) model can be expressed as:

$$h_{11,t} = c_{11}^2 + c_{21}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1}, \tag{4}$$

$$h_{22,t} = c_{22}^2 + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2 h_{22,t-1}, \tag{5}$$

where $h_{11,t}$ denotes the conditional variance for world crude oil market returns at time t, $h_{12,t}$ describes the conditional covariance between oil market returns and those of a corresponding sector market, and $h_{22,t}$ denotes the conditional variance of those sector index returns. In addition, the parameters a_{12}, a_{21}, b_{12}, b_{21} reveal how shock and volatility are transmitted over time and between crude oil market and Korean sector stock markets. The off-diagonal elements of matrices A and B capture cross-market effects, such as shock spillovers (a_{12} and a_{21}) and volatility spillovers (b_{12} and b_{21}).

The parameters of the bivariate GARCH model can be estimated by the maximum likelihood estimation method optimized with the Berndt, Hall, Hall and Hausman (BHHH) algorithm. The conditional log likelihood function $L(\theta)$ is expressed as:

$$L(\theta) = -T\log 2\pi - 0.5\sum_{t=1}^{T}\log\left|H_t(\theta)\right| - 0.5\sum_{t=1}^{T}\varepsilon_t(\theta)' H_t^{-1}\varepsilon_t(\theta), \tag{6}$$

where T is number of observations and θ denotes the vector of all the unknown parameters.

3. Data and descriptive statistics

This study examines the volatility spillover effects between the crude oil price and KOSPI 200 sector indices and considers the weekly closing market price data (Friday-close) from January 3, 2000, to May 17, 2009. When a holiday occurs on a Friday, we use the values on the previous day of trading.[1] We consider the world crude oil price (WCO), obtained from the Energy Information Administration (EIA), and that weekly all countries spot price FOB (Freight on Board) is weighted by estimated export volume. The KOSPI 200 sector indices in this study consist of five industry sector markets: manufacturing industry (MI), finance (FIN), electricity & communication (EC), construction (CON), and service (SER). All KOSPI 200 sector indices were provided from the database of the Korea Exchange (KRX).

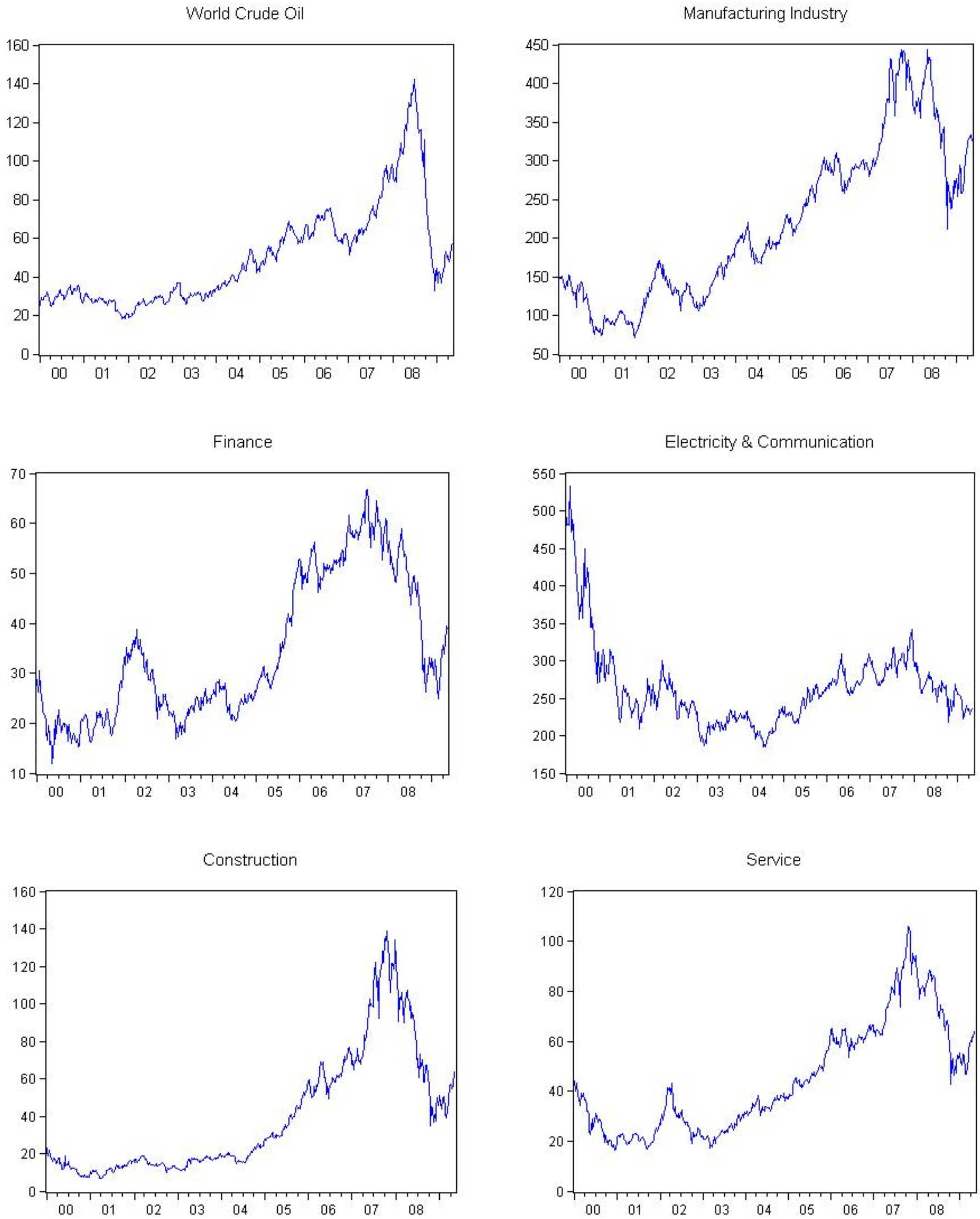
Figure 1 shows the dynamics of all sample prices. The increase in world crude prices was largely due to the economic growth in China and India until the July 2008 peak. Subsequently, remarkable price falls were observed from August 2008 to 2009 due to a drop in demand for energy commodity and the global financial crisis.

In addition, except for the electricity & communication sector, other industry sector indices display a similar price pattern during the sample period. The prices showed an

[1] The use of weekly prices in the analysis over the use of daily prices eliminates or significantly reduces any potential biases that may arise such as the bid-ask effect, non-trading days, etc.

upward trend until the middle of 2007 and a huge price drop due to the US financial crisis of 2008. The price decline of the electricity & communication sector was observed in early 2001, due to the IT dot-com bubbles.

<Figure 1> Dynamics of sample prices



The return series of the six prices are computed by $R_{i,t} = \ln\left(P_{i,t} / P_{i,t-1}\right) \times 100$, where $R_{i,t}$ denotes the continuously compounded returns for indices i at time t, and $P_{i,t}$ denotes the closing price of indices i at time t. Table 1 shows the descriptive statistics for the six sample return series. Apart from EC, the other sector returns showed a positive mean. The standard deviation (SD) of CON had the highest value, followed by MI and FIN. Based on the values of skewness (Skew.), excess kurtosis (Kurt.), and the Jarque-Bera (J-B) statistics, all of the return series followed a leptokurtic distribution, which has a higher peak and fatter tail than a normal distribution. The calculated values of Ljung-Box test statistic, $LB^2(24)$, for the squared return series were extremely high, indicating the rejection of the null hypothesis of no serial correlation. These results are in favor of a model that incorporates ARCH/GARCH features.

<Table 1> Descriptive statistics of sample returns

	WCO	MI	FIN	EC	CON	SER
Mean	0.180	0.161	0.062	-0.149	0.203	0.082
S.D.	4.409	0.592	5.798	3.776	7.298	5.321
Max.	22.10	24.90	26.89	14.03	42.97	20.07
Min.	-17.02	-24.65	-21.99	-14.49	-30.60	-26.30
Skew.	-0.475	-0.202	0.039	-0.294	0.181	-0.498
Kurt.	5.012	6.855	4.872	4.851	6.750	6.334
J-B	100.91***	306.3***	71.52***	76.85***	289.2***	246.7***
$LB^2(24)$	125.64 [0.000]	109.24 [0.000]	245.04 [0.000]	235.67 [0.000]	130.14 [0.000]	87.64 [0.000]

Notes: The Jarque-Bera (J-B) corresponds to the test statistic for the null hypothesis of normality in the sample return distributions. The Ljung-Box test statistic, $LB^2(24)$, checks for the serial correlation of the squared return residuals for up to the 24th order. *** indicates a rejection of the null hypothesis at the 1% significance level.

4. Empirical results

4.1 Volatility spillover effect between oil and sector stock markets

We investigate the volatility spillover between returns in five sector indices and oil price. In order to examine the volatility spillover effect, we employ the five bivariate GARCH (1,1) models based on the BEKK approach. The estimation results of the BEKK model are reported in Table 2. The modeled pairs are: world crude oil market-manufacturing industry (WCO-MI), world crude oil market-finance (WCO-FIN), world crude oil market-electricity & communication (WCO-EC), world crude oil market-construction (WCO-CON), and world crude oil market-service (WCO-SER).

As mentioned earlier, the diagonal elements (a_{11} and a_{22}) in matrix A capture the own past shock (news) effect, while the diagonal elements (b_{11} and b_{22}) in matrix B measure the own past volatility effect. The off-diagonal elements of matrices A and B capture cross-market spillover effects, such as shock (unexpected news), spillover (a_{12} and a_{21}), and volatility spillover (b_{12} and b_{21}).

To check the accuracy of the model specifications, we employ two diagnostic tests: the LM ARCH statistics, $ARCH_i(5)$, for standardized residuals; and the Ljung-Box statistic, $LB_i^2(24)$, for squared standardized residuals. Note that the $ARCH_i(5)$ test statistic checks the remaining ARCH effect in standardized residuals and the $LB_i^2(32)$ test statistic checks for the serial correlation of squared standardized residuals. The insignificance of $ARCH_i(5)$ and $LB_i^2(24)$ statistics indicates the appropriateness of the bivariate GARCH-BEKK model.

Beginning with the oil market-manufacturing industry (**WCO-MI)** pair, the estimation results indicate that the volatility of oil price returns is significantly affected by its own news and its past volatility, due to the significance of coefficients a_{11} and b_{11}. Additionally, the volatility of the manufacturing industry sector is indirectly affected by the unexpected oil market news and the past conditional variance of oil market, as indicated by the significant coefficients a_{12} and b_{12}. In fact, it appears that the manufacturing industry sector market is significantly sensitive to crude oil price.

While the volatility of returns in the manufacturing industry sector market is affected by its own news and volatility, its volatility is affected by weak evidence of a news impact of oil market returns. Thus, the volatility changes of the manufacturing industry sector market depend on unexpected oil market news and volatility. When oil price rises unexpectedly, the performance of manufacturing firms becomes more risky, which may due to greater oil demand. For the sake of the stable management, these firms have developed strategies for effective risk hedge of the impacts of oil market volatility in terms of oil futures or derivatives contracts.

From the oil market-finance industry (WCO-FIN) pair, the volatility of oil market returns is directly affected by its own news and volatility, and indirectly affected by the unexpected news and the past conditional variance of finance industry. However, while the volatility of returns in the finance sector is affected by its own news and volatility, no evidence of impacts of oil market volatility is detected. Thus, the finance sector, including insurance, securities and banks, etc., is well insulated from oil market volatility changes. As argued by Ewing, Forbes and Payne (2003), the finance sector returns have the least volatile response to macroeconomic shocks, such as monetary policy, economic growth, and a measure of the risk premium, than other industry sectors.

The oil market-electricity & communication sector (WCO-EC) pair reveals that the volatility of returns in the electricity & communication sector is weakly affected by the oil market news, but there is no evidence of an impact of oil market volatility. This finding indicates that although oil price changes play a role in systematic risk, the volatility changes of the electricity & communication sector (e.g., IT firms) are consistent with microeconomic factors, such as the development of new technology, price competition, and marketing strategy, etc. However, the oil return volatility is affected by the news and volatility of the electricity & communication sector.

In the results from the oil market-construction sector (WCO-CON) pair, we found that the oil market volatility is affected by news and volatility of the construction sector, and is also affected by its own news and volatility. The activity of construction sector firms (e.g., construction and machinery) affects the demand of energy usage (i.e., oil and petroleum products). Additionally, the volatility of the construction sector is affected by volatility in oil market. Increased volatility in the oil market is often considered as a greater uncertainty in the aggregate economy. In this point, the performance of construction sector firms is dependent on oil price changes.

Finally, the results of the oil market-service sector (WCO-SER) pair suggest that oil market volatility is affected by its own news and volatility, and it is also affected by the return volatility of the service sector. Likewise, the volatility of service sector market returns has a significant impact on oil market shock and volatility. One of the reasons for this finding is that the service sector covers many businesses that are related to energy-related expenditures by households, such as automobiles, retail, health care, and consumer staples (e.g., food and clothing), etc. It is apparent that increased volatility in oil market induces high inflation and recession in the aggregate economy. In this sense, households cannot afford to purchase the service sector products. Thus, the performance of these firms is dependent on the oil price changes.

In summary, our empirical results suggest that there is transmission of volatility and shocks between oil market and some of the sector stock markets. This volatility transmission provides an important guideline on cross-market hedging, optimal risk portfolios, and changes in common information.

4.2 Optimal portfolio weights and hedge ratios

Our previous findings suggest that the volatility transmission across oil market and sector stock markets is a crucial element for efficient diversified portfolios and risk management. Practically, portfolio managers are required to quantify the optimal weights and hedge ratios in order to effectively hedge oil price change risk. For minimizing the risk without reducing expected returns, we now consider a portfolio construction of oil price and stock sector indices. Following Kroner and Ng (1998), the portfolio optimal weights of oil asset and sector stock holding is given by:

$$w_t^{SO} = \frac{h_t^S - h_t^{OS}}{h_t^O - 2h_t^{OS} + h_t^S}. \tag{7}$$

And

<Table 2> Estimation results of the GARCH-BEKK model

Parameters	WCO-MI		WCO-FIN		WCO-EC		WCO-CON		WCO-SER	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Panel A: GARCH(1,1)-BEKK estimations										
A	0.358**	(0.182)	0.329	(0.178)	0.286	(0.179)	0.218	(0.186)	0.337	(0.179)
B	0.283	(0.171)	0.222	(0.198)	-0.085	(0.148)	0.671***	(0.263)	0.357	(0.201)
c_{11}	0.916***	(0.358)	1.081***	(0.281)	0.999***	(0.229)	0.613	(0.386)	0.806**	(0.287)
c_{21}	0.651***	(0.228)	-0.206	(0.239)	-0.263	(0.162)	1.465***	(0.402)	0.713***	(0.233)
c_{22}	-0.001	(0.005)	0.483***	(0.205)	0.086	(0.569)	-0.001***	(0.000)	-0.001	(0.001)
a_{11}	0.239***	(0.037)	0.269***	(0.033)	0.249***	(0.045)	0.101***	(0.037)	0.247***	(0.032)
a_{12}	0.126***	(0.041)	0.036	(0.039)	0.059**	(0.026)	0.094	(0.053)	0.127***	(0.041)
a_{21}	-0.104**	(0.051)	-0.120***	(0.042)	-0.192***	(0.051)	-0.081***	(0.031)	-0.078**	(0.037)
a_{22}	0.328***	(0.062)	0.267***	(0.039)	0.161***	(0.034)	0.381***	(0.045)	0.288***	(0.062)
b_{11}	0.943***	(0.023)	0.920***	(0.025)	0.929***	(0.019)	0.945***	(0.018)	0.948***	(0.022)
b_{12}	-0.069***	(0.021)	-0.002	(0.023)	-0.007	(0.011)	-0.302***	(0.040)	-0.070***	(0.019)
b_{21}	0.042	(0.031)	0.035***	(0.011)	0.039***	(0.014)	0.137***	(0.019)	0.030**	(0.015)
b_{22}	0.928***	(0.023)	0.959***	(0.011)	0.981***	(0.007)	0.889***	(0.023)	0.942***	(0.021)
Panel B: Diagnostic tests										
$LB_1^2(24)$	13.55	[0.956]	24.73	[0.420]	19.05	[0.746]	14.57	[0.932]	15.03	[0.919]
$LB_2^2(24)$	22.25	[0.564]	10.71	[0.991]	27.33	[0.289]	22.52	[0.548]	20.33	[0.677]
$ARCH_1(5)$	0.308	[0.907]	0.781	[0.563]	0.595	[0.703]	0.286	[0.920]	0.290	[0.918]
$ARCH_2(5)$	1.632	[0.149]	0.877	[0.496]	0.676	[0.746]	0.966	[0.437]	1.607	[0.156]
LogL	-2806.46		-2904.96		-2709.40		-3013.63		-2864.92	

Notes: P-values are in brackets and standard errors are in parenthesis. The $ARCH_i(5)$ test statistics check the remaining ARCH effects in standardized residuals. The $LB_i^2(24)$ test statistics check for the serial correlation of squared standardized residuals. ** and *** indicate significance at the 5% and 1% levels, respectively.

$$w_t^{SO} = \begin{cases} 0, & if \quad w_t^{OS} < 0 \\ w_t^{OS}, & if \ 0 \le w_t^{OS} \le 1 \\ 1, & if \quad w_t^{OS} > 1 \end{cases} \tag{8}$$

where w_t^{SO} refers to the weight of oil asset in a one-dollar portfolio of the two assets defined above at time t, h_t^S and h_t^O are the conditional variances of the sector stock index and the oil price, respectively, and h_t^{OS} is the conditional covariance between oil price and sector stock returns at time t. The optimal weight of the sector stock index in the considered portfolio is obtained by computing this amount $\left(1 - w_t^{SO}\right)$.

As for hedge ratios, Kroner and Sultan (1993) considered the conditional volatility estimates. For minimizing the risk of this portfolio (oil and sector stock markets), we measure how much a long position (buy) of one dollar in the oil market should be hedged by a short position (sell) of β_t dollar in the sector stock index, that is:

$$\beta_t^{OS} = \frac{h_t^{SO}}{h_t^S}. \tag{9}$$

Table 3 reports summary statistics for portfolio weights between oil and sector stock markets. The highest average value of w_t^{SO} (optimal weights) for the WCO-CON portfolio is 0.68, indicating that the optimal weight of oil asset holding is 68% and the remaining proportion of 32% is invested in the construction sector stocks. The lowest average optimal weight for the WCO-EC portfolio is 0.39, suggesting that 39% should be invested in oil asset and the remaining proportion of 61% invested in the electricity & communication sector.

<Table 3> Optimal portfolio weights for oil and sector stock markets

	Mean	St. Dev	Min	Max
WCO-MI	0.478	0.144	0.102	0.872
WCO-FIN	0.577	0.122	0.311	0.904
WCO-EC	0.390	0.101	0.139	0.646
WCO-CON	0.678	0.107	0.974	0.440
WCO-SER	0.537	0.147	0.198	0.935

Table 4 shows the average optimal hedge ratios between oil and sector stock markets. In general, the low ratios suggest that the oil price change risk can be effectively hedged by taking a short position in sector stock markets. These hedge ratios range from 0.12 (construction sector) to 0.08 (electricity & communication sector). For example, the largest ratio, 0.080, is for the WCO-EC portfolio, meaning that one-dollar long position (buy) in oil asset should be shorted (sold) by 8% of the electricity & communication sector. Among all the pairs of oil asset and sector stocks, the most effective strategy to hedge the exposure to oil price risk is to short stocks of the construction sector.

In summary, our findings provide an important guideline on building optimal risk portfolios between oil and sector stock markets and some benefits from the optimal diversifiable portfolio to minimizing the oil price risk without any impairment of expected returns.

<Table 4> Hedge ratio for oil asset and sector stocks

	Mean	St. Dev	Min	Max
WCO-MI	0.020	0.164	-0.495	0.493
WCO-FIN	0.013	0.107	-0.281	0.346
WCO-EC	0.080	0.143	-0.469	0.317
WCO-CON	0.012	0.103	-0.414	0.389
WCO-SER	0.044	0.161	-0.388	0.610

5. Conclusions

This paper investigated the transmission of volatility and shocks between world oil price and five sector stock indices of Korea using a bivariate GARCH model. We raised the question of whether all sector stocks have a homogenous impact from the volatility of oil price. We also analyzed the optimal weights and hedge ratio for building optimal portfolios to minimize the exposure to oil price risk.

Our empirical results point to the existence of significant shock and volatility spillovers across oil and sector stock markets, but a heterogeneous impact from oil price. For example, since the high oil price increases an input product cost, the manufacturing industry sector stocks are significantly sensitive to the oil price changes. Both construction and service sector stocks are also dependent on the oil price changes because a rise in oil price induces high inflation and recession in the aggregate economy. However, both the finance and electricity & communication sectors are well insulated from oil market volatility changes. In addition, our examination of optimal weights suggests that adding the oil asset into a well-diversified portfolio leads to the improvement of its overall risk-adjusted return performance. Likewise, our hedge ratios between oil and sector stock markets permit us to effectively hedge the oil price risk using the short position of sector stock indices.

These findings are of practical importance to financial market participants and may be useful in making optimal portfolio allocation decisions and developing cross-market hedging strategies.

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