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Return and Volatility Transmission Between Oil Prices and Emerging Asian Markets*

SANG HOON KANG**
Pusan National University
Busan, Korea

SEONG-MIN YOON***
Pusan National University
Busan, Korea

Abstract

We investigated return and volatility transmission between oil futures prices and ten Asian emerging indices using a VAR-bivariate GARCH model. We also analyzed the optimal weights and hedge ratios for optimizing portfolios to minimize the exposure to risk associated with oil futures price changes. We found no significant influence of oil futures price returns on Asian stock returns. However, strong volatility spillover was observed from oil futures price shocks and volatility to counterpart volatilities. In addition, optimal weights and hedge ratios suggested that incorporating the oil asset in a well-diversified portfolio effectively hedged the risks associated with oil price volatility.

Keywords: cross-market hedging, oil price risk, portfolio diversification, spillovers

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** Associate Professor, Department of Business Administration, Pusan National University, Busan, 609-735, Korea. E-mail address: sanghoonkang@pusan.ac.kr

*** Corresponding author. Professor, Department of Economics, Pusan National University, Jangjeon2-Dong, Geumjeong-Gu, Busan, 609-735, Korea. Tel.: +82-51-510-2557; Fax: +82-51-581-3143. E-mail address: smyoon@pusan.ac.kr (S.-M. Yoon).

INTRODUCTION

Recent oil price fluctuations have reinvigorated interest in the way that oil price shocks influence 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 variations and stock markets is an ongoing issue in energy finance. Basic theory suggests that the value of a stock equals the discounted sum of estimated 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 (Apergis and Miller 2009; Masih, Peters, and De Mello 2011).

Many studies have provided an explanation of the linkage between oil prices and stock market indices. The majority of these studies show the negative influence 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 oil price shocks may lead input prices to increase, thereby driving profits and returns in different countries or industries, or even within individual 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. However, there is a positive relationship between the oil price and the stock prices of oil companies (Sadorsky 2001; Boyer and Filion 2007; El-Sharif et al. 2005), indicating that oil price increases may also lead to higher stock prices for oil-related firms.

Given the recent uncertainties in oil prices, dynamic volatility spillover between oil markets and stock markets is of increasing interest for optimization of 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 sector-specific stock prices. Malik and Ewing (2009) focused on the volatility spillover between oil prices and several US sector indices (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 found little evidence of volatility spillover.

Arouri, Jouini, and Nguyen (2011, 2012) examined the extent of volatility transmission, portfolio designs, and hedging effectiveness in oil and sector stock returns in Europe and the US. They found significant evidence of unidirectional volatility spillover from oil to Europe sector stock returns; however, the empirical evidence supported 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 and technology companies using various multivariate GARCH models. In this case, technology stock prices exerted a greater influence than oil prices on clean energy stock prices.

This study contributes to the extant literature by investigating the linkage between oil price futures and ten emerging Asian stock markets using a VAR(1)-bivariate GARCH(1,1) model with the BEKK framework. An assessment of the return and volatility linkage between oil price volatility and sector price volatility is crucial for making investment decisions and for implementing appropriate policies for controlling the exposure to oil price risk in Asian stock markets.

The main contribution of this study is twofold. First, although previous empirical studies have documented the influence of oil price movements on stock returns in developed countries, little attention has been given to examining the return and volatility transmission between oil futures prices and Asian stock indices. Fluctuation in the price of crude oil strongly influences Asian economic growth and stock market prices; inversely, most Asian countries, which are heavy oil consumers, influence oil price fluctuations. In this study, we examined the return and volatility spillovers between oil futures and Asian stock markets. Second, we examined optimal portfolio designs and hedge ratios using the estimated conditional covariances between oil futures and Asian stock returns. From a portfolio management perspective, accurate estimation of the time-varying covariance matrix enables better financial and strategic decision-making regarding accurate asset pricing, risk management, and portfolio allocation. Our findings regarding optimal weights and hedge ratios indicated that investors can make appropriate capital budgeting decisions and effectively manage the exposure to oil price risk in the Asian stock markets.

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.

METHODOLOGY

VAR(1)-Bivariate GARCH(1,1) Model

Substantial attention has been given to how news from one market affects the volatility process of another market. The univariate GARCH model of Bollerslev (1986) has been extended to the multivariate GARCH model with a cross-conditional variance equation. In this study, we analyzed the mean and volatility spillovers using a VAR(1)-bivariate GARCH(1,1) model with the BEKK parameterization (Engle and Kroner 1995).

First, we considered the bivariate mean model, i.e., the VAR(1) process:

$$\begin{bmatrix} R_{1,t} \\ R_{2,t} \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} R_{1,t-1} \\ R_{2,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \tag{1}$$

$$\begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} | \Omega_{t-1} \sim N(0, H_t), \tag{2}$$

where H_t is a 2×2 corresponding conditional variance-covariance matrix. The market information available at time $t-1$ is represented by the information set Ω_{t-1}. The parameter β_{ij} corresponds to the mean spillover effects. For example, both β_{11} and β_{22} indicate that market returns are affected by their own lag values, whereas both β_{12} and β_{21} represent the mean spillover effects between oil futures and stock markets.

The standard BEKK parameterization for the bivariate GARCH(1,1) model is written as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \text{, or} \tag{3}$$

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}, \tag{4}$$

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 that measures the extent to which conditional variances are correlated past squared errors. B is a 2×2 squared matrix of parameters that 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:

$$h_{11,t} = c_{11}^2 + c_{21}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2h_{22,t-1}, \tag{5}$$

and

$$h_{22,t} = c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2h_{22,t-1}, \tag{6}$$

where the parameters a_{12}, a_{21}, b_{12}, b_{21} of equations (5) and (6) reveal how shock and volatility are transmitted over time and across markets. The off-diagonal elements of matrices A and B capture cross-market effects, such as shock spillover (a_{12} and a_{21}) and volatility spillover (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:

$$L(\theta) = -T\log 2\pi - 0.5\sum_{t=1}^{T}\log\left|H_t(\theta)\right| - 0.5\sum_{t=1}^{T}\varepsilon_t(\theta)' H_t^{-1}\varepsilon_t(\theta), \tag{7}$$

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

Optimal Portfolio Weights and Hedge Ratios

Understanding the volatility transmission across oil futures markets and stock markets is crucial for the efficient managing of diversified portfolios and risk management. Practically, portfolio managers are required to quantify the optimal weights and hedge ratios to effectively hedge risk associated with oil price fluctuations. To minimize the risk without reducing expected returns, we considered a portfolio constructed of oil futures prices and Asian emerging market indices. Following the method developed by Kroner and Ng (1998), the portfolio optimal weights of oil futures and stock indices holdings is given by:

$$w_t^{OS} = \frac{h_t^S - h_t^{OS}}{h_t^O - 2h_t^{OS} + h_t^S}. \tag{8}$$

and

$$w_t^{OS} = \begin{cases} 0, & if\ w_t^{OS} < 0 \\ w_t^{OS}, & if\ 0 \le w_t^{OS} \le 1, \\ 1, & if\ w_t^{OS} > 1 \end{cases} \tag{9}$$

where w_t^{OS} is the weight of an 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 stock index and the oil futures price, respectively, and h_t^{OS} is the conditional covariance between oil futures returns and stock returns at time *t*. The optimal weight of the stock index in the considered portfolio is obtained by computing the amount ($1 - w_t^{OS}$).

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

$$\beta_t^{OS} = \frac{h_t^{OS}}{h_t^{S}} . \tag{10}$$

DATA AND DESCRIPTIVE STATISTICS

This study considered weekly data (Friday to close) for a one-month sample oil futures contract at the West Texas Intermediate (WTIF) crude oil price and indices for ten emerging Asian markets (China, Hong Kong, India, Indonesia, Korea, Malaysia, the Philippines, Singapore, Taiwan, and Thailand). Weekly data covered the period from January 8, 1999, to May 18, 2012. Stock market indices were obtained from the MSCI database, while the WTI futures prices were extracted from the New York Mercantile Exchange (NYMEX). Figure 1 shows the sample price fluctuation over time for the markets evaluated. Similar price patterns were observed in each market. The increase in world crude prices was largely attributable to economic growth in Asia until the July 2008 peak. Price falls were then observed from August 2008 to 2009 due to a drop in demand for energy commodities and the global financial crisis. In addition, most stocks experienced similar price falls attributable to the global financial crisis of 2007 to 2009, which was sparked by the US subprime mortgage crisis.

The return series for all sample prices were computed by $R_{i,t} = \ln(P_{i,t}/P_{i,t-1}) \times 100$, where $R_{i,t}$ denotes the continuously compounded returns for each price *i* at time *t*, and $P_{i,t}$ denotes the closing price *i* at time *t*.

Table 1 summarizes the descriptive statistics and unit root tests for all sample return series. Panel A contains basic statistics for all return series. WTIF exhibited the highest average returns, which was not surprising in view of the overall increasing price of oil over

Figure 1. Dynamics of sample prices

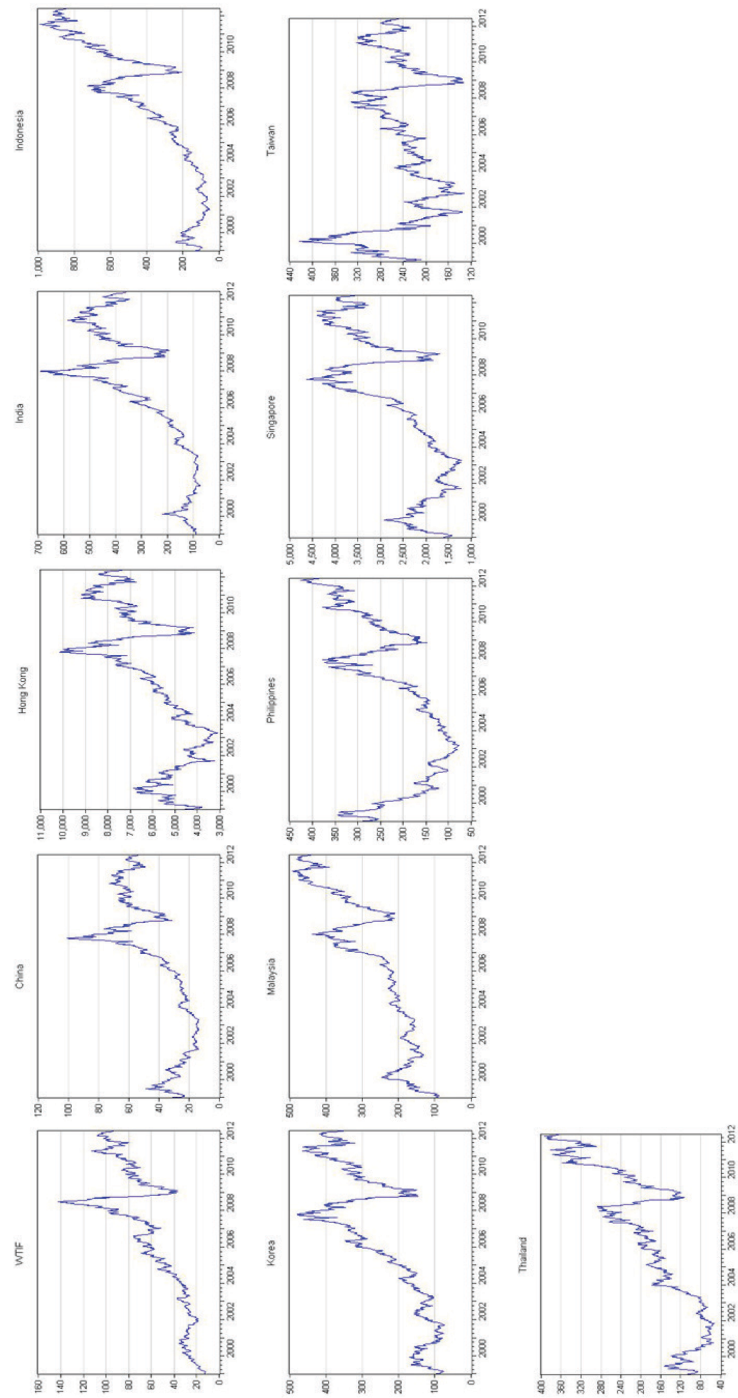


Table 1. Descriptive statistics of sample returns

	WTIF	China	Hong Kong	India	Indonesia	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand
Panel A: Descriptive statistics											
Mean	0.285	0.079	0.070	0.197	0.271	0.186	0.222	0.041	0.114	0.006	0.177
S.D.	4.268	4.535	3.274	4.223	5.179	5.078	2.868	3.650	3.358	3.923	4.407
Max.	15.53	17.93	9.823	18.37	21.54	28.63	14.37	15.24	18.51	19.36	17.26
Min.	-18.95	-22.13	-17.14	-21.88	-26.84	-27.90	-12.54	-20.80	-19.80	-14.40	-29.26
Skew.	-0.667	-0.369	-0.226	-0.491	-0.257	-0.289	0.273	-0.288	-0.439	-0.116	-0.516
Kurt.	5.049	4.791	4.372	5.355	5.556	6.465	6.894	5.553	7.929	4.883	7.055
J-B	174.01	109.24	60.74	189.43	197.83	358.95	449.69	199.36	729.18	104.71	509.40
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$LB^2(24)$	234.76	141.59	262.92	186.38	142.07	292.82	246.68	69.39	181.58	88.18	68.20
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Panel B: Unit root tests											
ADF	-22.44	-27.09	-26.11	-15.77	-12.55	-27.94	-24.46	-25.67	-25.20	-26.73	-13.72
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
PP	-22.44	-27.11	-26.28	-24.82	-26.56	-27.93	-24.81	-25.78	-25.40	-26.78	-26.54
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: The Jarque-Bera (J-B) value 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 up to the 24^{th} order. *** indicates a rejection of the null hypothesis at the 1% significance level.

the past decade. Except in the case of Malaysia, the skewness (Skew.) was negative for all sample returns, which suggested that extremely negative returns were likely for the stock and oil markets, respectively. Excess kurtosis (Kurt.) coefficients had significant values, indicating that outliers may have occurred with a probability higher than that of a normal distribution. Accordingly, the Jarque-Bera (J-B) test rejected the null hypothesis of normality for all sample returns at the 1% significance level. As also shown in Panel A, the calculated values of the 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 consistent with a model that incorporates typical ARCH/GARCH features.

Panel B presents the test for the presence of a unit root in the returns of oil futures and stock market indices using the Augumented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Both the ADF and PP unit root tests have the same null hypothesis, namely, that a time series contains a unit root. As shown in Panel B, large negative values for the ADF and PP test statistics rejected the null hypothesis of a unit root at the 1% significance level, indicating that all sample returns were stationary.

EMPIRICAL RESULTS

The Spillover Effect Between Oil Futures and Asian Stock Markets

We investigated the mean and volatility spillover effects between oil futures and ten Asian stock markets. To examine the spillover effect, we employed the VAR(1)-bivariate GARCH(1,1) model based on the BEKK approach. The estimation results of the VAR(1)-bivariate GARCH (1,1) model are presented in table 2.

Close inspection of the mean equations for all pairs showed that the one period with lagging oil future returns, denoted by β_{11} coefficients, significantly influenced current oil returns in all cases. This finding, which indicates some evidence of short-term predictability in oil price changes over time, is inconsistent with the weak-form efficiency of international oil markets (Serletis and Andreadis 2004; Tabak and Cajueiro 2007; Elder and Serletis 2008; Arouri et al. 2010, 2011). On the contrary, none of the β_{22} stock market coefficients were significantly different from zero, thus implying that past stock returns do not enable prediction of current stock returns in all cases.

The significance of coefficient β_{12} indicated an interdependence of returns in mean equations. We found that lagged stock returns significantly influenced oil futures returns in all sample cases. Stock returns positively influenced oil markets, because economic growth in oil-importing Asian countries demanded more oil production. However, except in India, the insignificance of coefficient β_{21} suggested that oil futures returns did not significantly influence emerging Asian market indices. As a result, with respect to the mean spillover effect, previous stock returns in Asian stock markets significantly and positively influenced oil futures returns, but the influence of the oil futures market on Asian stock markets was almost absent.

With respect to conditional variance equations, the estimation results indicated that the ARCH and GARCH coefficient estimates were significant at conventional levels in most cases. Except in the WTIF-Philippines case, the significance of the ARCH term indicated that the current conditional volatility of Asian emerging stock markets depended on past shocks affecting the return dynamics. Moreover, the sensitivity to past conditional volatility (the GARCH-term) was significant for all countries, thereby suggesting that the past value of the conditional volatility in Asian emerging markets was an important component for predicting their future volatility.

The volatility spillover effects between oil and stock markets in the Asian emerging countries were next considered. We first investigated the shock spillover effect between oil and stock markets. The significance of a_{21} coefficients indicated shock spillover from oil market to stock market in six cases: China, Hong Kong, Indonesia, Malaysia, the Philippines, and Taiwan. This finding indicates that past oil shocks significantly influenced stock market volatility. Moreover, except in Singapore and Taiwan, we observed that past oil volatility strongly influenced stock market volatility. Thus, our empirical results suggested shock and volatility spillovers from the oil market to emerging Asian stock markets.

The accuracy of the model specifications was evaluated using two diagnostic tests on residuals: the Ljung-Box statistic, $LB_i^2(24)$; and the LM ARCH statistics, $ARCH_i(10)$. The $LB_i^2(24)$ test statistic checks for serial correlation of squared standardized residuals, and the $ARCH_i(10)$ test statistic checks the remaining ARCH effect in stan-

Table 2. Estimation results of the GARCH-BEKK model

Parameters	WTIF-China		WTIF-Hong Kong		WTIF-India		WTIF-Indonesia		WTIF-Korea	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Mean equation										
μ_{10}	0.236	(0.159)	0.233	(0.159)	0.222	(0.160)	0.226	(0.160)	0.228	(0.159)
β_{11}	0.147***	(0.038)	0.141***	(0.038)	0.148**	(0.037)	0.147***	(0.038)	0.146***	(0.038)
β_{12}	0.074**	(0.036)	0.156***	(0.049)	0.102**	(0.038)	0.064**	(0.031)	0.073**	(0.038)
μ_{20}	0.190	(0.135)	0.152	(0.100)	0.163	(0.160)	0.253	(0.197)	0.179	(0.193)
β_{21}	0.078	(0.040)	0.046	(0.029)	0.074**	(0.037)	0.057	(0.047)	0.071	(0.045)
β_{22}	-0.039	(0.038)	-0.001	(0.038)	0.061	(0.061)	0.003	(0.038)	-0.069	(0.038)
Variance equation										
c_{11}	0.737***	(0.193)	0.401	(0.363)	0.588**	(0.266)	-0.308	(0.309)	0.549**	(0.237)
c_{21}	0.211	(0.241)	-0.177	(0.658)	0.122	(0.514)	1.078***	(0.216)	0.167	(0.560)
c_{22}	0.512	(0.872)	-0.559**	(0.266)	0.823***	(0.155)	-0.000	(0.140)	0.961***	(0.164)
a_{11}	0.221***	(0.028)	0.179***	(0.034)	0.150***	(0.053)	0.136***	(0.029)	0.172***	(0.029)
a_{12}	0.063	(0.038)	-0.034	(0.038)	-0.025	(0.089)	-0.104	(0.062)	0.020	(0.048)
a_{21}	-0.151***	(0.030)	0.141***	(0.052)	0.087	(0.062)	0.068**	(0.028)	0.019	(0.032)
a_{22}	0.246***	(0.035)	0.369***	(0.035)	0.355***	(0.041)	0.350***	(0.037)	0.399***	(0.035)
b_{11}	0.944***	(0.012)	0.976***	(0.012)	0.976***	(0.013)	0.989***	(0.008)	0.979***	(0.012)
b_{12}	-0.017	(0.015)	0.041	(0.021)	0.031	(0.029)	0.091***	(0.031)	0.037	(0.026)
b_{21}	0.038***	(0.011)	-0.097***	(0.024)	-0.059***	(0.023)	-0.058***	(0.013)	-0.035***	(0.013)
b_{22}	0.959***	(0.011)	0.909***	(0.015)	0.914***	(0.017)	0.902***	(0.018)	0.895***	(0.017)
Diagnostic tests										
$LB_1^2(24)$	11.09 [0.988]		12.84 [0.968]		12.97 [0.966]		19.09 [0.747]		26.11 [0.347]	
$LB_2^2(24)$	23.35 [0.499]		28.48 [0.240]		19.63 [0.717]		8.046 [0.999]		14.29 [0.939]	
$ARCH_1(10)$	0.026 [1.000]		0.588 [0.824]		0.480 [0.903]		0.793 [0.634]		0.718 [0.708]	
$ARCH_2(10)$	0.844 [0.586]		1.233 [0.265]		0.609 [0.807]		0.165 [0.998]		0.642 [0.778]	

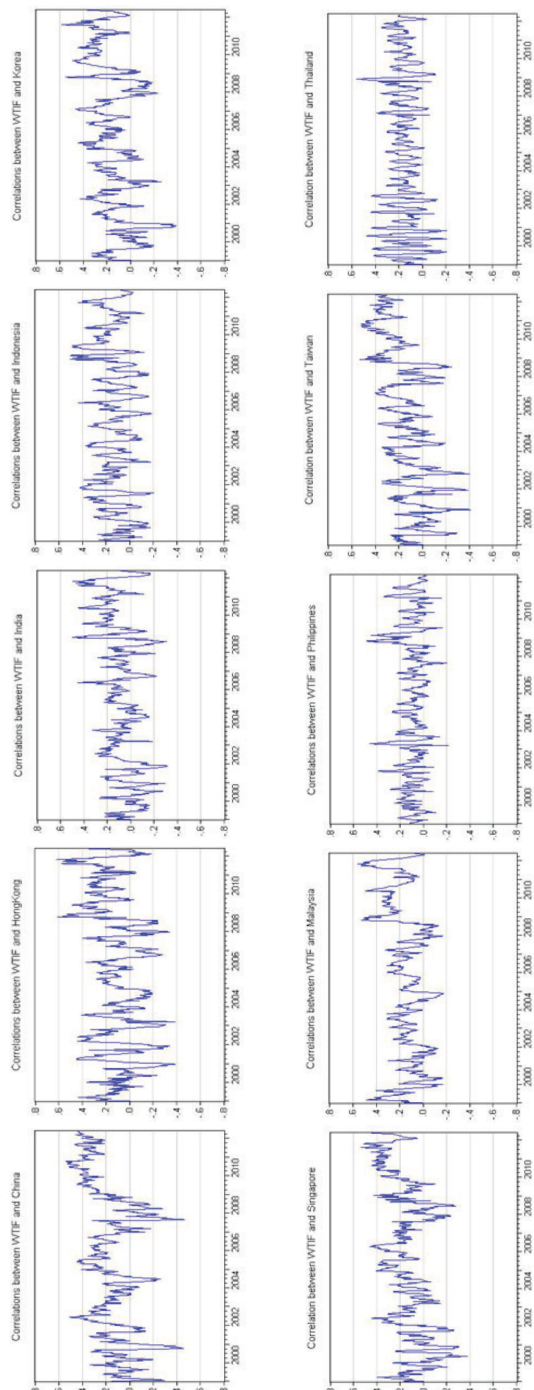
Notes: P-values are in brackets and standard errors are in parenthesis. ** and *** indicate significance at the 5% and 1% levels, respectively.

Table 2. (continued)

Parameters	WTIF-Malaysia		WTIF-Philippines		WTIF-Singapore		WTIF-Taiwan		WTIF-Thailand	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Mean equation										
μ_{10}	0.222	(0.160)	0.239	(0.160)	0.226	(0.159)	0.241	(0.160)	0.225	(0.159)
β_{11}	0.149***	(0.037)	0.155***	(0.038)	0.138***	(0.038)	0.149***	(0.038)	0.141***	(0.037)
β_{12}	0.086	(0.056)	0.039	(0.044)	0.155***	(0.048)	0.065	(0.041)	0.107***	(0.037)
μ_{20}	0.202	(0.109)	0.031	(0.138)	0.100	(0.127)	-0.005	(0149)	0.182	(0.168)
β_{21}	0.019	(0.026)	0.027	(0.033)	0.032	(0.030)	0.039	(0.035)	-0.008	(0.039)
β_{22}	0.067	(0.038)	0.019	(0.038)	0.036	(0.038)	-0.021	(0.038)	-0.007	(0.038)
Variance equation										
c_{11}	0.568***	(0.207)	0.879**	(0.403)	0.864***	(0.209)	0.718***	(0.182)	0.591***	(0.172)
c_{21}	0.026	(0.133)	-1.138***	(0.275)	0.571	(0.353)	0.339	(0.299)	0.913***	(0.276)
c_{22}	-0.289***	(0.064)	0.000	(0.205)	0.604**	(0.281)	0.492***	(0.174)	0.000	(0.156)
a_{11}	0.159***	(0.031)	0.029	(0.045)	0.226***	(0.028)	0.226***	(0.025)	0.085**	(0.034)
a_{12}	0.002	(0.018)	0.274***	(0.033)	0.069**	(0.032)	0.065**	(0.033)	0.106***	(0.027)
a_{21}	0.111***	(0.038)	0.119**	(0.060)	-0.053	(0.063)	-0.157***	(0.047)	-0.071	(0.051)
a_{22}	0.260***	(0.034)	0.059	(0.046)	0.358***	(0.047)	0.257***	(0.046)	0.265***	(0.035)
b_{11}	0.976***	(0.011)	0.931***	(0.034)	0.953***	(0.015)	0.948***	(0.010)	0.949***	(0.012)
b_{12}	0.007	(0.006)	-0.069***	(0.024)	-0.019	(0.029)	-0.014	(0.015)	-0.157***	(0.015)
b_{21}	-0.042***	(0.012)	0.219***	(0.040)	-0.016	(0.030)	0.029	(0.017)	0.136***	(0.019)
b_{22}	0.959***	(0.009)	0.901***	(0.036)	0.896***	(0.027)	0.952***	(0.014)	0.944***	(0.020)
Diagnostic tests										
$LB_1^2(24)$	13.06 [0.965]		14.40 [0.937]		13.70 [0.953]		16.85 [0.854]		12.67 [0.971]	
$LB_2^2(24)$	18.00 [0.803]		24.86 [0.413]		18.59 [0.774]		19.28 [0.736]		22.51 [0.549]	
$ARCH_1(10)$	0.537 [0.864]		0.595 [0.818]		0.818 [0.611]		1.217 [0.276]		0.382 [0.954]	
$ARCH_2(10)$	0.292 [0.983]		1.050 [0.399]		0.726 [0.700]		1.217 [0.276]		0.472 [0.908]	

Notes: P-values are in brackets and standard errors are in parenthesis. ** and *** indicate significance at the 5% and 1% levels, respectively.

Figure 2. Time-varying conditional correlation coefficients between oil futures and emerging Asian market indices



dardized residuals. In this study, the insignificance of both $LB_i^2(24)$ and $ARCH_i(5)$ statistics indicates the appropriateness of the VAR(1)-bivariate GARCH(1,1) model.

Figure 2 presents the conditional correlations of oil futures and stock markets estimated by the VAR(1)-bivariate GARCH(1,1) model, which were calculated as $h_{1,2} / \sqrt{h_{1,1}}\sqrt{h_{2,2}}$. The correlation coefficients were not constant; they varied greatly over time in all sample periods. The correlation trend provides a guideline for portfolio diversification. For example, the WTIF-China pair correlations exhibited a slight upwards (positive) trend after 2008, thus indicating that there is little scope for portfolio diversification between these two series.

In summary, our empirical results suggested that there is transmission of volatility and shocks from oil futures markets to some of the emerging Asian stock markets. This volatility transmission provides an important guideline for cross-market hedging, optimization of risk portfolios, and changes in common information.

Optimal Portfolio Weights and Hedge Ratios

Our previous findings suggested that the volatility transmission across oil markets and sector stock markets is crucial for efficient diversification of portfolios and risk management. Practically, portfolio managers seek to quantify the optimal weights and hedge ratios to effectively hedge risks associated with oil price fluctuations. In this context, we now consider a portfolio composed of oil futures and stocks to minimize the exposed risk without reducing expected returns.

Table 3 presents summary statistics for portfolio weights between oil futures and sector stock markets. The highest average W_t^{OS} value (optimal weight) was observed for the WTIF-Indonesia portfolio (0.592). In this case, the results indicate that the optimal proportion of oil futures in the portfolio is 59%, and that the remaining 41% should be invested in the stock market. The lowest average optimal weight was observed for the WTIF-Malaysia portfolio (0.265); in this case, the results suggest that 27% should be invested in oil futures and 73% should be invested in the stock market.

Table 4 presents the average optimal hedge ratios between oil futures and emerging Asian stock markets, and figure 3 pres-

Table 3. Optimal portfolio weights for oil and sector stock markets (values indicate optimal proportion of oil futures)

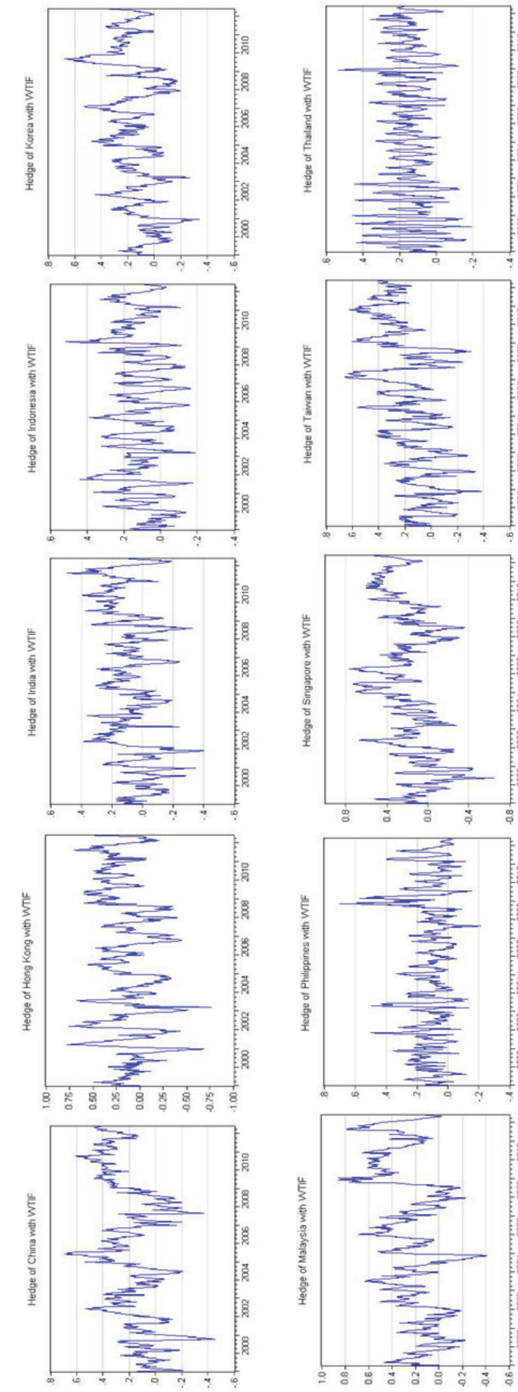
	Mean	St. Dev	Min	Max
WTIF-China	0.510	0.131	0.000	0.813
WTIF-Hong Kong	0.359	0.129	0.000	0.791
WTIF-India	0.489	0.126	0.000	0.903
WTIF-Indonesia	0.592	0.126	0.000	0.966
WTIF-Korea	0.563	0.151	0.000	1.073
WTIF-Malaysia	0.265	0.141	0.000	0.728
WTIF Philippines	0.425	0.077	0.000	0.715
WTIF-Singapore	0.345	0.139	0.000	0.865
WTIF-Taiwan	0.444	0.125	0.000	0.753
WTIF-Thailand	0.434	0.263	0.000	0.261

Table 4. Hedge ratios for oil assets and Asian indices

	Mean	St. Dev	Min	Max
WTIF-China	0.186	0.202	-0.454	0.689
WTIF-Hong Kong	0.129	0.266	-0.762	0.771
WTIF-India	0.076	0.154	-0.403	0.489
WTIF-Indonesia	0.112	0.126	-0.187	0.517
WTIF-Korea	0.145	0.171	-0.341	0.677
WTIF-Malaysia	0.237	0.237	-0.413	0.859
WTIF Philippines	0.111	0.124	-0.213	0.700
WTIF-Singapore	0.191	0.249	-0.646	0.767
WTIF-Taiwan	0.176	0.211	-0.385	0.659
WTIF-Thailand	0.152	0.119	-0.191	0.533

ents time-varying hedge ratios for each pair. The optimal hedge ratios range from a maximum value of 0.859 (WTIF-Malaysia) to a minimum value of -0.762 (WTIF-Hong Kong). The low ratios suggest that the oil futures price change risk can be effectively hedged by taking a short position in stock markets. In this study, the largest average hedge ratio (the most expensive hedge) was observed for the WTIF-Malaysia case (0.237). This value indicates that a one-dollar long position (buy) in oil futures should be shorted (sold) by a 24-cent investment in the stock market. In contrast, the lowest average hedge ratio observed, 0.076 (WTIF-India), implies that a one-dollar long in oil futures should be hedged with a short position of less than 8 cents in the stock market. Taken together, the results suggest that the most effective strategy for hedging the risk

Figure 3. Time-varying hedge ratios



associated with oil price fluctuation is to short invest in the Indian stock market.

In summary, our findings provide an important guideline for optimizing risk portfolios between oil futures and Asian stock markets, and we suggest a method for optimizing portfolio diversification to minimize the oil price risk without reducing expected returns.

CONCLUSIONS

In this study, we investigated the transmission of price returns and volatility between oil futures and ten emerging Asian stock markets using a VAR(1)-bivariate GARCH(1,1) model. We also analyzed the optimal weights and hedge ratios for optimizing portfolios to minimize the exposure to oil price risk.

Our empirical results are summarized as follows. First, oil returns did not influence Asian stock returns, but stock returns positively influenced oil futures returns due to economic growth in oil-importing Asian countries. Second, we observed strong evidence of volatility and shock transmission from the oil futures market to some of the emerging Asian stock markets. Third, our examination of optimal weights suggested that adding oil assets to a well-diversified portfolio improves overall risk-adjusted return performance. Likewise, hedge ratios between oil futures and stock markets suggested that effective hedging of the oil price risk could be accomplished by taking a short position in Asian stock markets.

These findings are of practical importance to financial market participants and may be useful for making optimal portfolio allocation decisions and developing cross-market hedging strategies. Using oil futures contracts, portfolio investors might reduce their exposure to oil risk in their Asian investments.

A limitation of our study is that the bivariate GARCH model used in this paper does not account for different volatility regimes, which are common during financial crises. Ignoring different transition periods may lead to spurious results, especially regarding the spillover effect in the markets (Gallo and Otranto 2008; Aloui and Jammazi 2009). We suggest that this research may be extended in a future study to investigate the spillover effect with regimes using a Markov switching approach (Hamilton 1989).

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