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The Relationship between Oil Price and OECD Stock Markets: A Multivariate Approach

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Abstract

In this paper, we consider the models that provide evidence of volatility transmission between oil and equity markets. Our aim is to complement previous research by addressing the dynamics of volatility transmission by using the multivariate dynamic conditional correlation–GARCH (DCC-GARCH) model of Engle (2002). This model helps detect eventual volatility spillovers, which are typically observed in stock markets and oil prices. Our sample consists of monthly frequency stock indexes and oil prices covering 10 OECD countries for the January 1990–December 2012 period. We show that oil price shocks in periods of world turmoil and political events have an important impact on the relationship between oil and stock market prices.

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1. Introduction

The study of the volatility spillover between the oil and stock markets is crucial for energy policy planning, portfolio diversification, and energy risk management (Awartani and Maghyereh 2013). Furthermore, the volatility transmission mechanism delivers important insights for the design of accurate models of stock valuation and risk premiums.

In this paper, we consider the models that provide evidence of volatility transmission between oil and equity markets. Our objective is to complement previous research by addressing the dynamics of volatility transmission by using the multivariate dynamic conditional correlation–GARCH (DCC-GARCH) model of Engle (2002), which can detect the dynamic correlations of volatility spillover transmissions. This multivariate framework is more suitable than a bivariate framework because it accounts for the dynamic interactions between all the variables included in the system. Several MGARCH models have been developed to capture the conditional heteroskedasticity of financial return series. Examples of the most commonly used models include the constant conditional correlation–GARCH (CCC-GARCH) model of Bollerslev (1990), the full parameterized BEKK-GARCH model of Engle and Kroner (1995), and the DCC-GARCH model of Engle (2002). It is commonly accepted that the CCC-GARCH allows for considerable reduction in the number of parameters to be estimated compared with the BEKK-GARCH, but a major drawback of this model is that it also imposes constancy of conditional correlations between innovations, as compared with the DCC-GARCH. Thus, we decided to adopt the multivariate DCC-GARCH model to gauge the time variations of the variance–covariance matrix and conditional correlations. These classes of models are distinguished by their simplicity and efficacy when estimating a large conditional covariance matrix because each return series is allowed to follow a univariate GARCH specification.

Although previous empirical studies have addressed this topic, only a few articles (Creti *et al*., 2013; Filis *et al*., 2011) have examined it in a multivariate framework. Recent literature on volatility transmission and measurement has included models that link oil and stock markets by taking into account their comovements. Hammoudeh *et al.* (2004) investigate spillover effects, day effects, and dynamic relationships among five daily S&P oil sector stock indices and five daily oil prices for the U.S. oil markets using both cointegration techniques and ARCH-type models. They show evidence of volatility spillovers from the oil futures market and stock returns of some oil sectors. Chiou and Lee (2009) examine the asymmetric effects of WTI daily oil prices on S&P 500 stock returns. Using the Autoregressive Conditional Jump Intensity model with expected, unexpected, and negative unexpected oil price fluctuations, they find that high fluctuations in oil prices have asymmetric unexpected effects on stock returns. Malik and Ewing (2009) examine bivariate GARCH models to estimate the volatility transmission between weekly WTI oil prices and equity sector returns and find evidence of spillover mechanisms. Choi and Hammoudeh (2010) extend the time-varying correlations analysis by considering commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index. They show that commodity correlations have increased since 2003, limiting hedging substitutability in portfolios. More recently, Arouri *et al.* (2010) examine the relationship between oil prices and 12 stock sectors in European countries. They show that the reaction of sector returns to changes in oil prices differs considerably across sectors and that the inclusion of oil assets into a portfolio of sector stocks helps improve the portfolio's risk–return characteristics.

Awartani and Maghyereh (2013) investigate return and volatility spillover effects between the oil market and the Gulf Cooperation Countries (GCC) stock markets by using indices proposed by Diebold and Yilmaz (2009, 2012), revealing transmission in both directions between 2004 and 2012. They find that the information flow from oil returns and volatilities to the GCC stock exchanges is important while the flow in the opposite direction is marginal. Moreover, the oil market gives other markets more than it receives in terms of returns and volatilities. These trends were more pronounced in the aftermath of the global financial crisis in 2008, and the net contribution of oil has intensified after a burst during the crisis. The empirical evidence from the sample is consistent with a case in which oil plays the dominant role in the information transmission mechanism between oil and equities in the GCC countries.

To examine the volatility spillover effects among more than two assets and measure volatility spillover between oil and stock markets, research has employed the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) methodology but has found increased problems in the parameter estimation due to the increased complexity (Fan and Zhang 2003). Thus, model estimation methods for the GARCH family models have been developed. Bollerslev *et al*. (1988) propose the VECH-GARCH model, which simplifies the multivariate model but cannot ensure that the conditional variance matrix is a positive definite matrix. The constant conditional correlation (CCC-GARCH) process of Bollerslev (1990) has succeeded in reducing the number of the parameters in the model but cannot describe the time-varying correlation. The full parameterized BEKK-GARCH model of Engle and Kroner (1995) ensures that the conditional variance matrix is a positive definite matrix but cannot be reasonably explained by economic theories.

After developing the CCC model, Engle (2002) developed the Dynamic Conditional Correlation (DCC) model, which can describe the time-varying correlations and be explained reasonably by economic theories. The major innovation in DCC is the use of a two-step estimation method to overcome the computation complexity involved in the parameter estimation of multivariate GARCH models, in addition to allowing for a consistent estimation of the time-varying correlation matrix (Engle 2002). Furthermore, in DCC-GARCH, any type of GARCH family models with stationary covariance and normally distributed errors can be used to model the volatility of the return rate of a certain single asset. Thus, DCC is more flexible in modeling the volatility of asset return rates and can help select the most accurate model to describe the volatilities.

First, we test whether there is shift-contagion effect of the financial crisis on OECD stock markets or whether there are only interdependencies. Second, we implement this empirical approach on an updated data set covering the major OECD stock markets.

The paper is organized as follows: The second section describes the methodology employed. In the third section, we present the data and report the empirical results. We conclude in the last section.

2. Methodology

To illustrate the dynamic conditional correlation model for our purposes, let X_t be an (11×11) vector (10 OECD countries and oil price) containing the return, volume, and implied volatility series in a conditional mean equation as follows:

$$\begin{aligned} X_t &= \mu_t + H_t^{1/2}\varepsilon_t \\ H_t &= D_t R_t D_t^{'} \\ R_t &= (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \\ D_t &= diag(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \cdots, \sqrt{h_{11,11,t}}) \end{aligned} \quad , \qquad (1)$$

where $X_t = (X_{1t}, X_{2t}, \cdots, X_{11t})$ is the vector of the past observations, $\mu_t = (\mu_{1t}, \mu_{2t}, \cdots, \mu_{11t})$ is the vector of the conditional returns, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \cdots, \varepsilon_{11t})$ is the vector of the standardized residuals, R_t is an (11×11) symmetric dynamic correlations matrix, and D_t is a diagonal matrix of conditional standard deviations for each of the return series, with $h_{ii,t} = w_i + \alpha_i \varepsilon_{ii,t-1}^2 + \beta_i h_{ii,t-1}$. In addition, Q_t is an (11×11) variance–covariance matrix of standardized residuals ($u_t = \varepsilon_t / \sqrt{h_t}$), which we define as follows :

$$Q_t = (1-\lambda_1-\mu_1)\overline{Q} + \lambda_1(\eta_{t-1}\eta'_{t-1}) + \mu_1 Q_{t-1},$$
(2)

where we calculate the covariance matrix, $\overline{Q}$, as a weighted average of $\overline{Q}$, the unconditional covariance of the standardized residuals; $\eta_{t-1}\eta'_{t-1}$ is a lagged function of the standardized residuals; and Q_{t-1} is the past realization of the conditional covariance. In the DCC specification, only the first lagged realization of the covariance of the standardized residuals and the conditional covariance are used. This requires the estimation of two additional parameters, λ_1 and μ_1.

For a pair of markets i and j, the conditional correlation at time t can be written as follows:

$$\rho_{ij,t} = \frac{(1-\theta_1-\theta_2)\overline{q}_{ij} + \theta_1 u_{i,t-1}u_{j,t-1} + \theta_2 q_{ij,t-1}}{\left[(1-\theta_1-\theta_2)\overline{q}_{ii} + \theta_1 u^2_{i,t-1} + \theta_2 q_{ii,t-1}\right]^{\frac{1}{2}}\left[(1-\theta_1-\theta_2)\overline{q}_{jj} + \theta_1 u^2_{j,t-1} + \theta_2 q_{jj,t-1}\right]^{\frac{1}{2}}}, \quad (3)$$

where q_{ij} is the element on the i^{th} line and i^{th} column of the matrix Q_t. We employ the QMLE method, introduced by Bollerslev and Wooldridge (1992), to estimate the vector of unknown parameters (θ).

3. Data and Empirical Results

3.1 Data description

The data set includes monthly stock market indices for 10 OECD countries and the Brent crude oil index from January 1, 1990 to December 1, 2012: United States (NASDAQ 100), Canada (TSX), France (CAC 40), Germany (DAX 30), Italy (Milan MIB), Spain (Madrid General Index, MGI), Denmark (KFX Copenhagen), United Kingdom (FTSE 100), Australia (All Ordinaries Index, AOI), and Japan (Nikkei 225). Our data set comes from Datastream and Morgan Stanley Capital International.

3.2. Estimation of dynamic correlation

Table 1 shows the estimation of the multivariate DCC-GARCH model. The coefficients in the table are significant and positive; they clearly indicate that the GARCH model captures volatility. All the estimated parameters are statistically significant at the 5% level. The GARCH error parameter α (when α is relatively large, for example, above 0.1, volatility is sensitive to market events) measures the reaction of conditional volatility to market shocks. In our case, α is above 0.1 for most countries, except for the United States, Canada, and Italy. The GARCH lag parameter β (when β is relatively large, for example, above 0.9, volatility takes a long time to diminish after a crisis in the market) measures the persistence of conditional volatility, regardless of anything happening in the market. In our case, β for all the countries is equivalent or close to 0.9, except for Japan.

Figure 1 identifies a first group of countries (United Kingdom, Australia, Japan, New Zealand, and the United States): all stock markets show a significant decrease in correlation coefficients between 1991 and 1992. This period is dominated by changes in the precautionary demand for crude oil because of the Iraq War (see Filis et *al.* 2011). In addition, during the Asian financial crisis of 1997–1998, correlations of the United Kingdom, Australia, Japan, New Zealand, and the United States with oil exhibited a low positive interdependence between oil prices and stock markets considered. Our results are consistent with those of Forbes and Rigobon (2002), who stress that the increased correlation during times of crises is due to increased volatility in global stock markets. Similarly, Longin and Solnik (1995) emphasize the instability of the relationship of correlations between international stock markets and observe that the volatility and correlations of stock markets rose significantly after the 1987 stock market crash. King *et al*. (1994), Ramchand and Susmel (1998), and Morana and Beltratti (2002) also confirm the positive relationship between volatility and correlations.

Nevertheless, in the 1990–2004 period, we observe a peak in correlation coefficients around the 2000 and 2001 for the majority of countries. The high positive correlation between oil and stock market prices occurred because of the high demand for oil due to the rapid increase in the housing market and construction industry, which arose from decreasing interest rates worldwide.

The next sub-period is between 2006 and 2008. The correlation coefficient showed an increasing and positive pattern for Australia, Japan, New Zealand, France, the United States, and Canada. This increase is explained by rising demand, mainly by China. This aggregate demand-side oil price shock was expected to have a positive effect on stock markets (both in oil-importing and oil-exporting countries) because it signaled an increase in world trade (mainly dominated by China). This result is in line with the findings of Kilian and Park (2009) and Filis *et al.* (2011), who suggest that aggregate demand-side oil price shocks originated by world economic growth have a positive impact on stock prices.

During the 2008–2010 sub-period, the coefficients of correlation were generally positive. The main event during this phase was the global financial crisis due to the export of U.S. mortgages to the rest of the world, such as asset-backed securities (Stiglitz 2009), which can be considered an aggregate demand-side oil shock (International Energy Agency 2009). Filis *et al.* (2011) explain that the positive correlation between oil prices and stock markets is due to the financial crisis, which caused both the entry of bearish stock markets into territories and the sharp drop in oil prices.

For Spain, Germany, and France, the Asian financial crisis produced a negative aggregate demand-side oil price shock, driving oil prices to lower levels (see Filis *et al.* 2011). The majority of stock markets in that period also experienced a small decline in or a stable performance. A peak in correlation coefficient is observed around 2006 for Spain, Germany, and France. Again, this high positive correlation between oil and stock market prices was caused by the high demand for oil due to the rapid increase in the housing market and construction industry. Hamilton (2009a), Kilian and Park (2009), and Filis *et al.* (2011) explain that the 2006–2008 sub-period was characterized by an increase in oil prices due to rising demand from world economic growth. This aggregate demand-side oil price shock was expected to have a positive effect on oil-importing countries.

Thus, two main conclusions can be drawn from our investigation. Oil price shocks in periods of world turmoil and political events have important impacts on the relationship between oil and stock market prices. Regarding the sign of this correlation, we find two trends: a negative one, similar to Filis *et al.* (2011), Hamilton (2009b), and Kilian and Park (2009), who argue that the first and second wars in Iraq and the terrorist attack on the United States caused a negative correlation between oil and stock markets, and a positive one, when aggregate demand-side oil price shocks (e.g., Asian crisis, Chinese economic growth, the global financial crisis) cause a significant, positive correlation between stock market prices and oil prices.

4. Conclusion

Empirical studies have documented that high oil prices can have a significant impact on stock market returns. In the same vein, we examined the impact of crude oil price fluctuations on

OECD stock market returns. Using monthly data of stock markets and oil prices from 10 OECD countries and the Brent crude oil index during the January 1, 1990–December 1, 2012 period, we employed Engle's (2002) multivariate GARCH-DCC to simultaneously estimate the conditional correlations between oil prices fluctuations and stock market returns. Our analysis shows that if the shock originates from demand, oil prices and stock markets tend to move together with varying degrees of strength in OECD countries, depending on the origin of the shock.

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Table 1: Estimation Results for DCC-GARCH

	Constant	α	β
USA (US)	0.015*	0.054*	0.941*
	(0.003)	(0.006)	(0.007)
CANADA (CAN)	0.012*	0.088*	0.902*
	(0.003)	(0.010)	(0.012)
AUSTRALIA (AUS)	0.008*	0.105*	0.888*
	(0.002)	(0.009)	(0.010)
GERMANY(DEU)	0.021*	0.098*	0.894*
	(0.004)	(0.010)	(0.010)
DENMARK (DNK)	0.024*	0.132*	0.861*
	(0.003)	(0.012)	(0.011)
SPAIN (ESP)	0.019*	0.117*	0.871*
	(0.003)	(0.011)	(0.012)
FRANCE (FRA)	0.017*	0.099*	0.893*
	(0.004)	(0.010)	(0.010)
UNITED KINGDOM (UK)	0.009*	0.109*	0.887*
	(0.002)	(0.011)	(0.010)
ITALY (ITA)	0.012*	0.088*	0.905*
	(0.002)	(0.008)	(0.009)
JAPAN (JPN)	2.845*	0.255*	0.527*
	(0.077)	(0.025)	(0.014)
	(0.010)	(0.013)	(0.014)
Oil	0.014*	0.095*	0.871*
	(0.003)	(0.012)	(0.017)

Notes: This table presents the estimation results of GARCH (1, 1). The numbers in parentheses represent associated standard errors. * Indicate that the coefficients are significant at the 5% level.

Figure1. Dynamic conditional correlations with Oil