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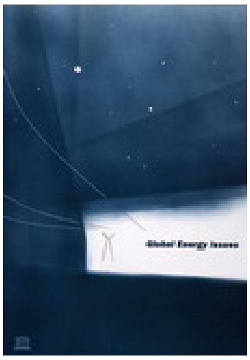

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Do oil prices predict the dynamics of equity market? Fresh evidence from DCC, ADCC and Go-GARCH models

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Abstract: This paper investigates the dynamic condition correlations between oil price, industrial production, short-term interest rates and equity market in South Korea using three types of GARCH models. The results from the DCC and ADCC GARCH models show strong evidence of significant dynamic conditional correlations suggesting higher long-term persistence of volatility than short-term persistence. The findings suggest, particularly, that oil prices have positive dynamic conditional correlations to equity markets, while the dynamic conditional correlations between equity market and short-term interest rates are significantly negative. These results have considerable economic implications. Firstly, oil price as a risk factor increases the equity market volatility. It also represents an implicit risk factor that cannot be diversified and which requires therefore to be hedged or priced. Secondly, the oil acts as an inflationary factor leading central banks to adjust their short-term interest rates in order to smooth the inflationary effect on both real economy and financial activity.

Keywords: oil price; equity market; industrial production; short-term interest rates; dynamic conditional correlations.

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1 Introduction

South Korea is the 12th largest economy in the world. Being one of the four 'Asian dragons', the country experienced a rapid growth and integration into the world economy in the last fifty years. As a leader in new technologies, South Korea is a giant economy that has just emerged. The country is vulnerable to external shocks. Now, it has a positive trade balance and a low unemployment rate. South Korea is a privileged observation post in terms of technology, information and communication. Since 2012, the country has suffered from a downturn in its economic transactions with China and the USA, which are its main trading partners. As a response to the slowdown in 2015, the government has put in place a recovery plan leading to a slight increase in the economic growth in 2016.

Several empirical studies have found a weak relation between oil price changes and the GDP growth rate after an oil-shock. According to Hamilton (1983), this may be due to an asymmetric relationship between the two variables. Numerous authors focused on the oil prices impact on both real economy and financial markets. Among others, Jones and Kaul (1996), Huang et al. (1996), Apergis and Miller (2009), Elyasiani et al. (2011), and Lee et al. (2012) document that oil prices have significant effects on financial markets. Notice that the nature of the impact remains conflicting and inconclusive, although the large number of previous studies reporting the negative impact of oil prices on the equity market. These mixed results are perhaps due to the heterogeneity of the sampled market and geographic area analysis. The disparity in oil price effects on equity markets may differ substantially on whether the sampled country is a net oil importer or a net oil exporter. It may also depend on the country economic growth and level of revenue. In addition, the country policy on oil grants may explain the sensitivity of real activities and financial market to changes in oil prices.

Over the last century, oil prices are experiencing sharp changes leading to important chocks. As oil constitutes a main resource in industrial production, these shocks are transmitted to equity market through both the real activity (real industrial production as a proxy) and financial channels (the short term interest rates). For instance, oil price acts as an inflationary factor, leading to high operating costs and leading central banks to adjust their short-term interest rates to smooth this inflationary impact. Different industries such as industrial production, transport, etc. are substantially affected by the volatility in oil prices. Therefore, the uncertainty in the oil market (supply and demand shocks) may significantly impact the economic growth and financial stock market development.

Much researches, such as those articulated by Jones and Kaul (1996), Sadorsky (1999), Mohanty et al. (2011), Nguyen and Bhatti (2012), Naifar and Al Dohaiman (2013), Chang and Yu (2013), among others, have been conducted to examine the nature of responses of equity markets to oil price fluctuations. However, even if the previous studies provide great important results, the impact of oil price shocks over time requires more investigation. Therefore, this paper attempts to examine the dynamic conditional correlations between oil price fluctuations and equity market returns by incorporating industrial production and short-term interest rates as main transmission channels of oil shocks to financial markets. We examine, particularly, the persistence of the transmission of volatility in both the short and the long-run. In this respect, we develop three GARCH model versions, namely the DCC, ADCC and GO-GARCH models, to better examine the symmetric and asymmetric conditional dynamic correlations between equity markets and oil price shocks taking into account both direct and indirect effects produced, and considering the real industrial activity index and the interest rates as main transmission channels.

The remainder of this paper proceeds as follows. Section 2 provides the main theoretical and empirical literature on the equity market – oil price dynamics. Section 3 focuses on the data and methodology. Section 4 summarises the main empirical finding and their discussion. Finally, the last section concludes the study.

2 Literature review

Several studies have focused on the oil price equity market dynamics. However, although the large number of studies conducted in this field the empirical results still mixed and conflicting across countries. Earlier studies conducted by Hamilton (1983, 2011) link financial crisis to oil price shocks. More particularly, Hamilton reported in 1983 that seven out eight financial crises are preceded by an oil price shock. He added in 2011 that 10 out 11 financial crises are preceded by an oil price shock.

In the previous literature on the stock market response to changes in oil prices three main results are commonly shown. Firstly, negative associations between equity markets and oil prices have been earlier confirmed by numerous authors for different economies such as O'Neil et al. (2008) for the US, UK and France, Park and Ratti (2008) for US and 12 European oil importing countries, and Nandha and Faff (2008) for global industry indices (except for attractive industries). In the same perspective, the results of Ciner (2001) show significant negative impacts of oil price shocks on real stock returns. His results show also strong evidences of nonlinearity in oil price shocks on stock returns. For Basher and Sadorsky (2006), the increase in oil prices plays strong role in raising inflation tax, risk and uncertainty leading therefore to lower wealth and serious reductions in stock prices. Empirical findings from the study of Sadorsky (2006) suggest significant responses of emerging stock markets to oil price risk. Issac and Ratti (2009) tested the long-run connections between world crude oil prices and real stock prices for six OECD countries over the period from January 1971 to March 2008 using a Vector Error Correction model. They found clear long-run negative response of real stock prices to changes in oil prices.

This negative association oil price shocks and equity markets can be explained in term of the direct effects of a rise in oil prices on future cash flows and inflation. From this perspective, Shimon and Raphael, (2006) show that oil price shocks result in a rise in inflation and unemployment and therefore lead to a sharp depression in economic growth and asset prices. This negative response may be due to the fact that the rise in oil prices increases the operating costs as oil constitutes a main input in industrial production, which induces consequently a reduction in the expected future incomes. Moreover, oil price changes can significantly influence the supply and demand for output at an industry sector and also at the whole economy and therefore decrease the firm incomes and performances. This can be attributed to the effect of the changes in oil prices on the discount rate for future income as a consequence of the direct effect these changes may exert on both the expected inflation rate and the expected real interest rate. Finally, the high volatility in oil prices as a source of uncertainty may lead industrial organisations to delay their irreversible investments as a reaction to the reduced expected profits (Bernanke, 1983; Pindyck, 1991).

Many other papers have investigated the predictive power of oil prices for the future stock market returns. Driesprong et al. (2008) examine whether oil price predict stock market returns for a large sample of developed and emerging countries. They found that oil price can significantly predict stock returns in 12 developed markets and in all the sampled emerging markets. Significant negative predictive power of lagged oil prices to stock return is also confirmed by Hong et al. (2002) for the US stock market. Taken together, these aforementioned results from Driesprong et al. (2008) and Hong et al. (2002) seem to confirm those reported in Papapetrou (2001) for the Greek stock market.

In contrast, strong evidences of positive and significant response of stock market prices to oil prices are supported by numerous authors such as Faff and Brailsford (1999), Sadorsky (2001), Abid et al. (2020a,b), among others. For instance, Abid et al. (2020a,b) used different GARCH model to explore the dynamic condition correlation between stock returns and a set of financial and macroeconomic variables including oil prices. Their results suggest positive dynamic conditional correlations and positive hedging ratios between oil prices and equity market, suggesting that oil has significant hedging effectiveness.

Other studies, conversely, suggest the absence of interdependence between equity and oil markets. Jones and Kaul (1996) used quarterly data for Canada, Japan, the UK and the US over the period from 1947 to 1991. Their findings suggest for the US and Canada significant responses of stock prices to oil price shocks. For Japan and the UK, the results suggest that oil prices do not impact the stock prices. Insignificant responses to oil price shocks are also suggested by many other studies. For instance, Chen et al. (1986) and Apergis and Miller (2009) suggest that the returns generated by oil price don’t have a significant impact on stock market indices. For Chen et al. (1986), the risks caused by the sharp changes in oil prices are without significant impacts on financial markets. For eight developed countries, Apergis and Miller (2009) findings suggest an insignificant effect of structural oil price shocks on stock prices.

Furthermore, different empirical approaches have been used to explore the oil price fluctuation-stock market returns dynamics such as Vector Autoregressive (VAR) model, co-integration, ARDL models, etc. and the results are mixed and conflicting. Huang et al. (1996) found that daily oil future returns are without significant effect on the broad-based market indexes such as the S&P 500 over the period 1979–1990. The results from the study of Sadorsky (1999) obtained using an unrestricted VAR model, including monthly data on oil prices, stock returns, short-term interest rate, and industrial production spanning the period from 1947 to 1996 show that oil price plays a pivotal role in explaining the US broad-based stock returns. These results confirm those previously found by Park and Ratti (2008) using data for the US and 13 European countries over the period from January 1986 to December 2005. Findings by Park and Ratti (2008) suggest that oil price shocks strongly impact the real stock returns either immediately or within one month.

Naifar and Al Dohaiman (2013) employed a Markov regime-switching model to examine the regime dynamics of stock market returns in response to change and volatility in oil price. They used two-state Markov switching models to explore the impacts in the crisis regime and the non-crisis regime. Their findings do not support regime dependence between oil market volatility and stock market returns in the GCC countries except to Oman. The results show, however, an asymmetric impact of crude oil price on inflation rates with a more pronounced impact magnitude of the positive response of inflation rate during crisis periods. The short term interest rate reacts also asymmetrically to changes in oil price, especially over crisis period.

Aloui and Jammazi (2009) used a two regime Markov switching EGARCH model to examine the response of French, Japanese and the UK stock market to changes in crude oil shocks over the period from January 1987 to December 2007. Their findings show a net dependence between oil prices and the volatility of real returns as well as the probability of transition across regimes.

Reboredo and Rivera-Castro (2014) used the wavelet multi-resolution analysis to examine the linkages between oil prices and a large aggregate stock market and industrial sectoral indices. Their results show a non-significant response of the stock market to changes in oil prices during the pre-crisis period. During the crisis period, positive responses of stock returns are, oppositely, observed.

In some recent studies such as those conducted by Dhaoui et al. (2018a, b) and Dhaoui et al. (2021), strong evidences of sensitive responses of stock prices (sectoral) to oil price shocks (demand and supply shocks) are particularly reported. The impact of oil price shocks depends specifically on the type of shocks (supply vs. demand shocks), the national vs. world specifications of oil prices, and on whether the country is a net oil importer or a net oil exporter. Oil prices are also found to affect asymmetrically stock market (Dhaoui et al. (2018a) and the impact are strongly sectoral dependent (Dhaoui et al., 2021).

3 Data and methodology

3.1 Data description

To examine the empirical linkages between oil price shocks and stock market prices in South Korea, we collect data for real stock prices (RSP), real industrial production (IP), nominal interest rates (INT) and oil prices (OP) over the period from January 1980 to December 2018. To compute the real stock price we report the stock price index to the inflation rate. For the nominal oil price, we use the WTI nominal price as a proxy. To compute the real national price, we deflate the product of the nominal oil price and the exchange rate to the consumer price index. To compute the world real oil price we report the nominal oil price to the US producer price index. Finally, we deflate the nominal industrial production to the consumer price index to calculate the real industrial production. Data for the stock market are available in "EUROSTAT" databases. The data for the oil price are available in the Energy Information Administration (EIA) database. Finally, the data for the rest of the variables are obtained from the "OECD" database and the Global Financial Data (GFD).

3.2 Estimates models specification

The aim of this study is to model volatilities and conditional correlations between real stock prices, industrial production, oil prices and nominal interest rate in South Korea. Hence, we employ the DCC model introduced by Engle (2002), the ADCC model developed by Cappiello et al. (2006), and the GO-GARCH model of Van der Weide (2002).

Based on the information set I_{t-1}, an AR(1) process for r_t, which is a $n \times 1$ vector of stock returns, can be written as follows:

$$r_t = \mu + ar_{t-1} + \varepsilon_t \tag{1}$$

The residuals term is illustrated as:

$$\varepsilon_t = H_t^{1/2} z_t \tag{2}$$

with H_t indicates the conditional covariance matrix of r_t and z_t denotes a $n \times 1$ vector i.i.d random vector of errors.

The DDC-GARCH model is estimated following these two steps:

1 Estimation of the GARCH parameters.

2 Estimation of the conditional correlations.

$$H_t = D_t R_t D_t \tag{3}$$

where H_t is a $n \times n$ matrix of conditional covariance, R_t indicates the conditional correlation matrix and D_t denotes a diagonal matrix with time varying standard deviations on the diagonal.

$$D_t = diag\left(h_{1,t}^{1/2}, \cdots, h_{n,t}^{1/2}\right) \tag{4}$$

$$R_t = diag\left(q_{1,t}^{1/2}, \cdots, h_{n,t}^{1/2}\right) Q_t diag\left(q_{1,t}^{1/2}, \cdots, h_{n,t}^{1/2}\right) \tag{5}$$

In equations (4) and (5), $h1,\ldots hn$ are the elements of the conditional covariance matrix and $q1$, ... qn are the elements of the conditional correlation matrix

Given that H is a diagonal matrix, the expressions for h are univariate GARCH models. The elements of H_t for the GARCH(1,1) model are presented as:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{6}$$

Q_t represents a symmetric positive definite matrix. It can be specified as:

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1 z_t z'_{t-1} + \theta_2 Q_{t-1} \tag{7}$$

$\bar{Q}$ represents the $n \times n$ unconditional correlation matrix of the standardised residuals $z_{i,t}$, knowing that $z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$ and θ_1 and θ_2 are non-negative parameters. In order to construct the dynamic conditional correlations, we use θ_1 and θ_2, which are associated with the exponential smoothing process. The DCC model is mean reverting as long as the sum of θ_1 and θ_2 is less than one. The correlation estimator $\rho_{i,j,t}$ can be written as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \tag{8}$$

Cappiello et al. (2006) introduce an Asymmetric DCC (ADCC) model based on the DCC model and the asymmetric GARCH model developed by Glosten et al. (1993) by adding an asymmetric term. Accordingly, the elements of the conditional covariance matrix H_t become:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t}^2 I(\varepsilon_{i,t-1}) \tag{9}$$

In this equation, $I(\varepsilon_{i,t-1})$ takes the value one if $\varepsilon_{i,t-1} < 0$ and 0 otherwise. If $d > 0$, hence the variance is more sensitive to negative rather than positive residuals. This asymmetric effect implies that bad news tend to increase volatility more than good news of the same magnitude.

The dynamics of Q for the ADCC model are specified as:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{Q}^{-}G) + A' z_{t-1} z'_{t-1} A + B' Q_{t-1} B + G' z_t^{-} z_t'^{-} G \tag{10}$$

In the above equation, A, B, and G are $n \times n$ parameter matrices and z_t^{-} denote zero-threshold standardised errors with a value equal to z_t in case of negative standardised errors and zero otherwise. $\bar{Q}$ and $\bar{Q}^{-}$ represent the unconditional matrices determined based on z_t and z_t^{-}, respectively.

Based on the GO-GARCH model, the returns r_t are the sum of the conditional mean (m_t), which can include an autoregressive term of order one (AR(1) term), and an error term (ε_t).

$$r_t = m_t + \varepsilon_t \tag{11}$$

In the GO-GARCH model, the difference between the returns and the conditional mean is mapped onto a set of unobservable independent factors denoted f_t.

$$\varepsilon_t = A f_t \tag{12}$$

In equation (12), A is a mixing matrix which can be decomposed into two matrices. The first is an unconditional covariance matrix denoted $\sum$ and the second is an orthogonal (rotational) matrix denoted U.

$$A = \Sigma^{1/2} U \tag{13}$$

The rows of this matrix correspond to the assets, and the columns correspond to the factors (f). The factors (f) can be written as:

$$f_t = H_t^{1/2} z_t \tag{14}$$

Where z_t is a random variable that has a mean of zero ($E(z_{it}) = 0$) and a variance of one ($E(z_{it}^2) = 1$). In this specification, a GARCH process can be adopted to model the factor conditional variances h_{it}. The unconditional distribution of factors must satisfy two conditions: $E(f_t) = 0$ and $E(f_t f`_t) = I$. By combining equations (11), (12) and (14) together, r_t can be specified as:

$$r_t = m_t + AH_t^{1/2} z_t \tag{15}$$

and the conditional covariance matrix of ($r_t - m_t$) is written as:

$$\Sigma_t = AH_t A' \tag{16}$$

For the GO-GARCH model, Van der Weide (2002) assumes that the mixing matrix A is a time invariant and H_t is a diagonal matrix. Additionally, the mixing matrix A must be orthogonal. Based on the studies of Broda and Paolella (2009) and Zhang and Chan (2009), the independent component analysis (ICA) is used to estimate the unconditional covariance matrix U.

4 Empirical results and discussion

The main aim of this section is to empirically examine the dynamic conditional correlation between real stock prices and three factors, namely the short-term interest rate, oil prices and industrial production index. This allows us better understanding the main key factor sensitively affecting the real stock prices and helps investor adjusting their trading strategies to cover their portfolio against higher volatility or selecting more diversified portfolios in order to better smooth the effect of exogenous shocks relating to oil prices (direct impact) and short-term interest rates and industrial production as the main transmission channels of oil price shocks to financial markets.

4.1 Data preliminary analysis

For the various sampled time series, we plotted the raw data in Figure 1. It is interesting to note that RSP and OP co-move closely during most of the time with strong trends up to the 2008-2009 financial crises. The IP series shows a sharp rise in 1990 and indicates a strong trend. The INT displays a significant decline during the sample period.

Figure 1 Time series plots

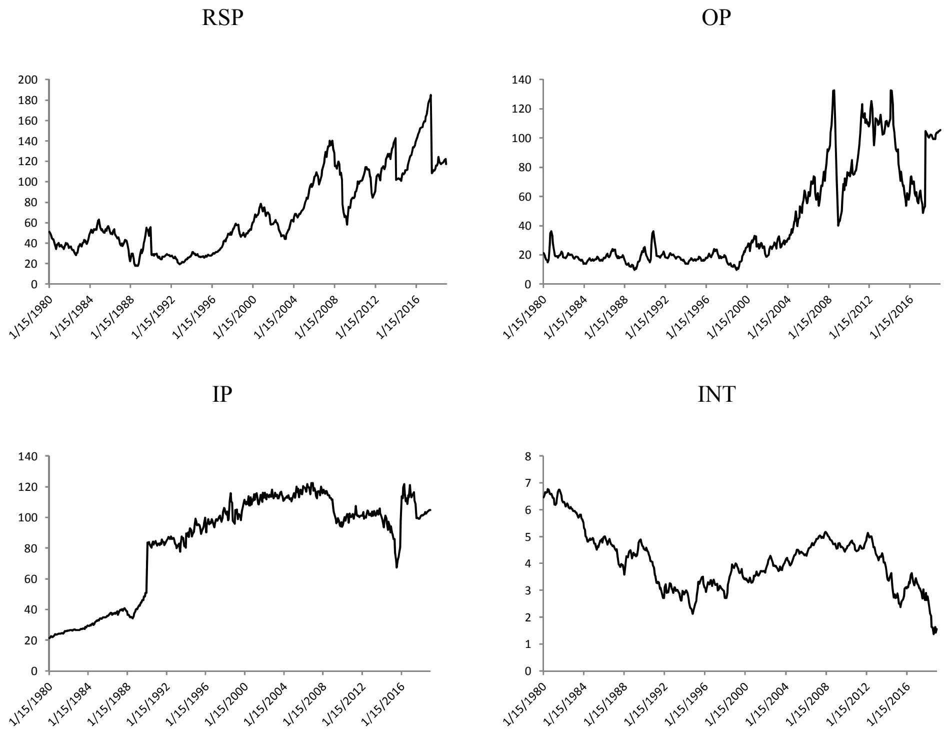


Table 1 reports the main summary statistics for the real stock price, the industrial production, the short-term interest rates and the real oil price. We see clearly that the real stock prices, the industrial production and the real oil price have a positive mean average, while the short-term interest rates have a negative mean average. We show also that the short-term interest rates exhibit higher standard deviation highlighting a high volatility over the sampled period. Conversely, the industrial production index has the lowest standard deviation. The JB statistics suggest that the different sampled time series are far away to be normally distributed as the respective p-values are strongly lower than 1% significance level. Finally, the ARCH(12) LM tests suggest strong evidence of ARCH effects.

Table 1 Summary statistics for monthly data

	RSP	*IP*	*INT*	*OP*
Nobs	468	468	468	468
Min	–66.6667	–11.3109	–41.3562	–31.0955
Max	20.5573	50.0895	124.1713	45.8950
Range	87.2240	61.4004	165.5275	76.9905
Median	1.0538	0.0855	–0.2721	0.1569
Mean	0.2869	0.3623	–0.3075	0.2040
SE.mean	0.3129	0.1827	0.4973	0.4197

Table 1 Summary statistics for monthly data (continued)

	RSP	*IP*	*INT*	*OP*
Var	43.9544	14.9910	111.0252	79.0754
Std.var	6.6298	3.8718	10.5368	8.8924
Coef.var	23.1064	10.6847	–34.2698	43.5970
J.B.	120	710	400	180
p-value	<0.0001	<0.0001	<0.0001	<0.0001
ARCH(12)	270	220	250	270
p-value	<0.0001	<0.0001	<0.0001	<0.0001

Notes: S.E, Var, Coef. Of Var, and Std. var., stand for standard errors, variance, coefficient of variance, and standard deviations. JB stats is the Jarque-Bera test with the null hypothesis of normality. ARCH is the auto-regressive heteroskedasticity test.***, **, and * indicate the rejection of respective null hypothesis at 10%, 5%, and 1% level of significance.

Table 2 reports the results outcome of the unit root tests. These results suggest the rejection of the null hypothesis of stationary at the level and we cannot reject this hypothesis in the first difference. Hence, all our sampled time series are I(1).

Table 2 Unit root tests

	ADF		*PP*		*KPSS*	
	In level	*In difference*	*In level*	*In difference*	*In level*	*In difference*
RSP	–1.3416	–9.5904***	–1.1605	–12.0778***	1.8180***	0.0643
IP	–2.4985	–6.8935***	–2.4721	–16.5818***	2.0891***	0.4330*
INT	–1.5292	–7.5598***	–1.7553	–11.3313***	1.8771***	0.0340
OP	–0.7213	–17.6940***	–0.7723	–17.6949***	0.3570*	0.2629

Notes: ADF, PP, and KPSS are the unit root tests. ***, **, and * indicate the rejection of the respective null hypothesis at 10%, 5%, and 1% level of significance.

Unconditional correlations summarised in Table 3 indicate that a positive and significant correlation between RSP and OP. However, RSP correlates negatively and significantly with INT and IP.

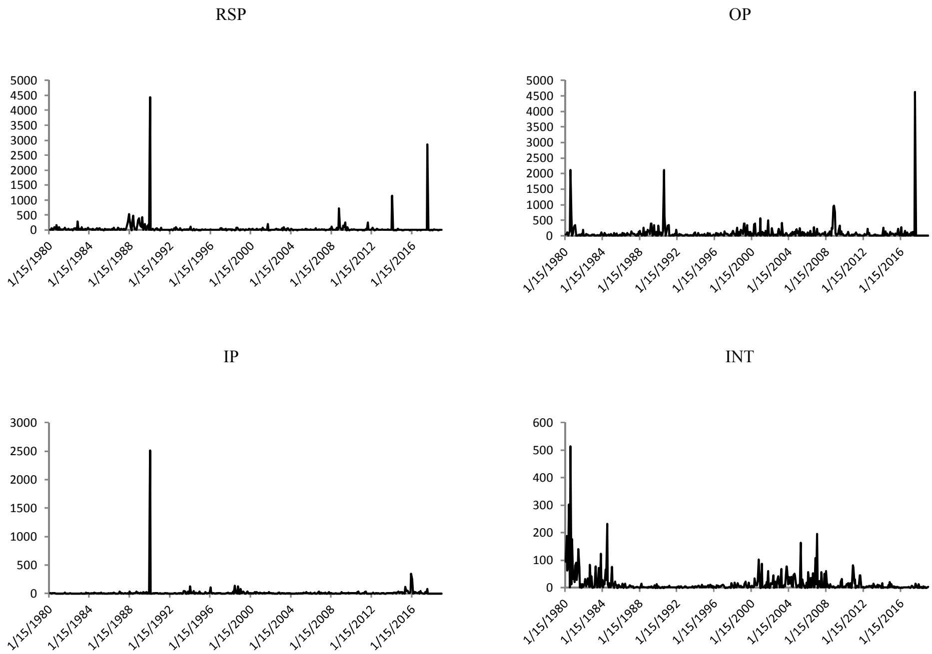
Table 3 Pearson correlations between monthly data

	RSP	*IP*	*INT*	*OP*
RSP	1			
IP	–0.2460 [a]	1		
INT	–0.3241 [a]	0.0854[c]	1	
OP	0.1215 [a]	0.0211[b]	–0.0240[c]	1

Notes: [a] $p < 0.01$, [b] $p < 0.05$, [c] $p < 0.1$.

Time series graphs of the squared monthly data, in Figure 2, show several volatility clustering. We see that RSP, IP and OP series have volatility clustering in 1990. Furthermore, OP and INT displays volatility between 1999 and 2009.

Figure 2 Squared monthly data



In order to fit the most appropriate version of DCC model, we adopt the model building strategy used by Basher and Sadorsky (2016). We estimate four versions of the DCC model and in each one we include a constant in the mean equation and a GARCH(1,1) variance equation. Adjustments were made with respect to including an AR(1) term in the mean equation and choice of distribution. Based on the results in Table 4 and using five model selection criteria (AIC, BIC, Shibta, HQ, and LL), we conclude that the DCC with an AR(1) term in the mean equation estimated with a multivariate t distribution is the best version.

Table 4 Four specifications for the DCC model

	DCC	*DCC*	*DCC*	*DCC*
AR(1)	Yes	No	Yes	No
Distribution	MVT	MVT	MVNORM	MVNORM
AIC	24.562	24.876	25.765	25.986
BIC	24.864	25.141	26.022	26.205
Shibata	24.552	24.868	25.758	25.981
HQ	24.681	24.981	25.866	26.072
LL	–5481	–5556	–5756	–5810
Nobs	449	449	449	449

Notes: AIC refers to Akaike criterion, BIC is the Bayes, H-Q is the Hannan–Quinn and LL is the Likelihood.

4.2 Regression results

In Table 5, we present the estimation of the DCC and ADCC parameters. The estimated coefficient of the AR(1) term (a) in the mean equation is positive and statistically significant in the RSP, INT and OP equations and negative and statistically significant in the IP equation (for DCC model). Except for the ADCC model in IP equation, we show a short-term persistence in each variable since the α term is statistically significant. Similarly, we find a long-term persistence in the RSP, IP and OP equations as the estimated coefficient on the β term is statistically significant. In these equations, the short-term persistence appears to be lower than the long-term persistence. The estimated asymmetric term γ is positive and significant only for IP, indicating that negative shocks tend to increase the variance more than positive shocks of the same magnitude. For the DCC model, we show that the estimates coefficient on θ_1 and θ_2 are both positive and significant at 1% significance level. In addition, the sum of these estimated coefficients is less than one, suggesting that the dynamic conditional correlations are mean reverting. However, the estimated coefficient on θ_1 is not significant. The shape parameter λ is equal to the degrees of freedom. As the number of freedom increase, the shape of the "t distribution" tends to the "normal" distribution. The results show that OP has the highest estimated shape parameter (over than 13). The RSP, IP and INT series have heavier tails (λ is between 2 and 4).

Table 5 DCC and ADCC parameter estimates

	DCC				*ADCC*			
	Coef.	*S.E.*	*t*	*Prob*	*Coef.*	*S.E.*	*t*	*Prob*
μ_{RSP}	1.2503	0.2979	4.1969	0.0000	1.2442	0.2994	4.1555	0.0000
a_{RSP}	0.2131	0.0516	4.1298	0.0000	0.2137	0.0513	4.1612	0.0000
ω_{RSP}	1.4252	2.0239	0.7041	0.4813	1.4248	2.0228	0.7043	0.4812
α_{RSP}	0.2907	0.0935	3.1070	0.0018	0.2747	0.1186	2.3146	0.0206
β_{RSP}	0.7082	0.0482	14.6689	0.0000	0.7048	0.0550	12.8129	0.0000
γ_{RSP}					0.0388	0.01305	0.2974	0.7661
λ_{RSP}	4.3824	0.8855	4.9486	0.0000	4.3789	0.9099	4.8122	0.0000
μ_{IP}	0.2208	0.0998	2.2118	0.0269	0.2024	0.1082	1.8714	0.0612
a_{IP}	–0.1703	0.0508	–3.3488	0.0008	–0.1041	0.0907	–1.1475	0.2511
ω_{IP}	1.7350	0.7042	2.4638	0.0137	0.3590	0.1546	2.3222	0.0202
α_{IP}	0.2467	0.0807	3.0558	0.0022	0.0017	0.0020	0.8831	0.3771
β_{IP}	0.6069	0.0791	7.6685	0.0000	0.8793	0.0267	32.8607	0.0000
γ_{IP}					0.2293	0.0604	3.7946	0.0001
λ_{IP}	4.6931	1.3024	3.6032	0.0003	4.4178	1.3360	3.3067	0.0009

Table 5 DCC and ADCC parameter estimates (continued)

	DCC				*ADCC*			
	Coef.	*S.E.*	*t*	*Prob*	*Coef.*	*S.E.*	*t*	*Prob*
μ_{INT}	–0.0066	0.3341	–0.0198	09841	–0.0009	0.3331	–0.0027	0.9978
a_{INT}	0.4727	0.05276	8.9597	0.0000	0.4743	0.0526	9.0128	0.0000
ω_{INT}	5.3334	14.2691	0.3737	0.7085	5.4353	15.0046	0.3622	0.7171
α_{INT}	0.5137	0.0985	5.2131	0.0000	0.5615	0.1226	4.5787	0.0000
β_{INT}	0.4853	0.4223	1.1489	0.2505	0.4827	0.4385	1.1007	0.2709
γ_{INT}					–0.0906	0.1830	–0.4953	0.6203
λ_{INT}	2.8872	0.2064	13.9872	0.0000	2.8861	0.2047	14.0937	0.0000
μ_{OP}	0.0870	0.4517	0.1926	0.8471	0.0273	0.4979	0.0550	0.9561
a_{OP}	0.2227	0.0496	4.4873	0.0000	0.2265	0.0512	4.4223	0.0000
ω_{OP}	5.2813	2.5590	2.0638	0.0390	4.9514	2.4697	2.0048	0.0449
α_{OP}	0.1463	0.0460	3.1765	0.0014	0.1225	0.0684	1.7903	0.0733
β_{OP}	0.7833	0.0529	14.7932	0.000	0.7940	0.0545	14.5439	0.0000
γ_{OP}					0.0348	0.0776	0.4481	0.6540
λ_{OP}	13.2847	6.8202	1.9478	0.0514	13.1345	6.6854	1.9646	0.0494
θ_1	0.0528	0.0163	3.2234	0.0012	0.0106	0.0152	0.7001	0.4838
θ_2	0.7989	0.0723	11.0482	0.0000	0.9721	0.0527	18.4133	0.0000
θ_3					6.0117	0.7957	7.5543	0.0000
λ	6.1768	0.7790	7.9283	0.0000				
AIC	24.562				24.586			
BIC	24.864				24.933			
Shibata	24.552				24.573			
HQ	24.681				24.723			
LL	–5481				–5482			
N. obs	449				449			

Notes: DCC and ADCC estimated using a multivariate normal (MVNORM) distribution. All specifications include a constant and an AR(1) term in the mean equation.

Table 6 The GO-GARCH estimates

		The rotation matrix U		
	U(1)	U(2)	U(3)	U(4)
U(1)	0.255	–0.935	–0.110	0.221
U(2)	0.482	0.232	–0.845	0.004
U(3)	0.722	0.243	0.481	0.434
U(4)	0.426	–0.115	0.207	–0.873
		The mixing matrix A		
	A(1)	A(2)	A(3)	A(4)
A(1)	5.517	–1.929	1.639	2.280
A(2)	0.258	–0.210	0.173	–3.847
A(3)	–0.297	9.994	0.526	–1.450
A(4)	3.715	0.139	–7.647	0.070
		GO-GARCH parameter estimates		
	F(1)	F(2)	F(3)	F(4)
ω	0.0794	0.0749	0.1756	0.1262
α	0.1675	0.5056	0.1421	0.2116
β	0.7479	0.4934	0.6846	0.6419
Skew	–0.2037	0.1347	0.0676	–0.1454
Shape	3.3478	0.3765	2.5710	0.8024
LL	–5506.16			

Notes: GO-GARCH estimated using a multivariate affine negative inverse Gaussian (MANIG) distribution. All specifications include a constant and an AR (1) term in the mean equation.

Table 6 shows the results of the GO-GARCH estimation. In this table, we present the results of the rotation matrix (U), the mixing matrix (A), and the parameter estimates. Since $U^TU=I$, the rotation matrix U is orthogonal. Expect the second factor, the estimated short-run persistence (α) is less than the long-run persistence (β) which is in conformity with DCC and ADCC models.

4.3 Dynamic conditional correlation

We constructed the one-step-ahead dynamic conditional correlations using rolling windows procedures. Particularly, we used a full sample of 4680 observations and produced 1000 one-step-ahead dynamic conditional correlations. We refit our estimated GARCH model every 20 observations. Figure 3 reports the one-step-ahead dynamic conditional correlations produced by DCC, ADD and GO-GARCH models. For the three couples RSP/Oil, RSP/IP, and RSP/RIP the two models DCC and ADCC-GARCH produce similar one-step-ahead dynamics. The GO-GARCH produces, however distinguishable dynamics compared to those produced by the DCC and ADCC models.

The dynamic conditional correlations between RSP and Oil are positive over the full sampled period for the three GARCH model types. This implies that oil price as a factor of risk and uncertainty cannot be diversified. Investors assimilate oil prices as a market risk which must be priced. When oil prices increase dramatically, investors require a risk premium to smooth their exposition to the risk generated by the impact of oil price changes on production costs and inflation. The magnitude of the correlation is higher over the post-subprime crisis period. This period is characterised by high uncertainty on oil prices. In fact, over the period from 2007 till 2018 many events are observed such as the sub-prime crisis (2007–2009), the Greece crises (started in 2009), the European Sovereign crisis (2010–2011), the Spring Arab revolution (December 2010, 2011), Spanish financial crisis (2008–2014), the ISIS attacks in Syria, Libya, etc. These events affect the supply/demand for oil and are therefore the origin of turbulence and of a sharp uncertainty in oil prices, which experienced as sharp increase (reaching 145 $/baril in July 2015) followed by a dramatic decrease (reaching lower than 36$/baril in January-February 2016).

The dynamic conditional correlations between RSP and INT are negative over the full sampled period. The increase in short-term interest rates reduces the net present value of assets as it increases the financial costs (increase in debt interest) and the discount rate which results in a reduction in the stock market prices. The negative dynamic conditional correlation between RSP and INT, may also be attributed to the lower interest rates, largely shown in most of the emerging and developed countries commonly known as the so-called "Bernanke put."

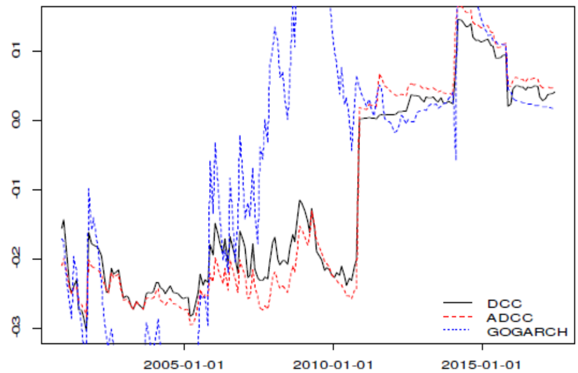
The dynamic conditional correlation between RSP and IP are negative over the period from late 2000 till the end of the year 2010. Over the period 2011–2018 positive dynamic conditional correlations are seen. The first sub-period is characterised by a sharp increase in oil prices, which lead to an increase in the operating costs as well as a high uncertainty due to the political (attacks of 11 September for example) and financial crisis (Subprime crisis). Over this period, the stock markets react more likely to non financial factors more than financial one. Over the second sub-period, the oil prices fall and the political and financial risks are smoothed as the attacks are oriented to some strategic regions such as the north of Africa (Lybia especially), West Asian region (Iraq and Syria, and Yemen).

Table 7 reports for each pair RSP/Oil, RSP/INT, and RSP/RIP, the correlation between dynamic conditional correlations produced by the three GARCH model specifications. We show, particularly, high correlation between the dynamic conditional correlations produced by the DCC and ADCC models. While the dynamic conditional correlations produced by the GO-GARCH model have low correlation with those produced by both the DCC and ADCC models. These results joint those produced by the one-step-ahead analysis plotted in Figure 3.

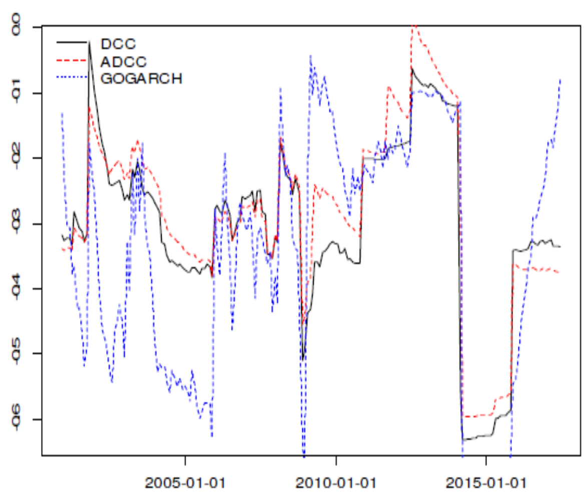
Table 7 Correlation between correlations

	RSP/IP	*RSP/INT*	*RSP/OP*
DCC/ADCC	0.9925	0.9531	0.9874
DCC/GO-GARCH	0.5624	0.7448	0.5004
ADCC/GO-GARCH	0.5290	0.7737	0.5523

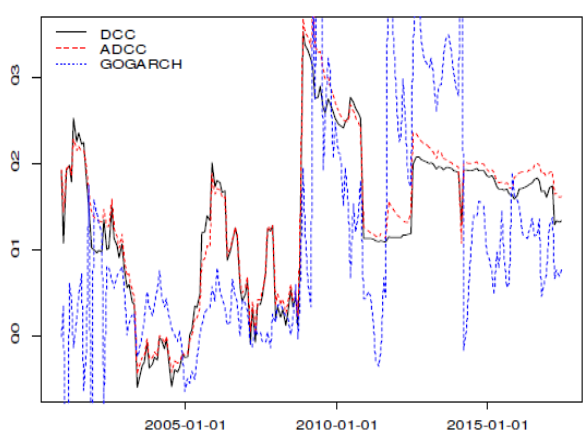
Figure 3 Rolling one-step-ahead conditional correlations



(a) Dynamic conditional correlations: RSP/IP



(b) Dynamic conditional correlations: RSP/INT



(c) Dynamic conditional correlations: RSP/OP

Overall, our results show high long-run persistence of oil price shocks to both the short-term interest rates and the industrial production. These results imply that oil price shocks are transmitted to equity market either directly and indirectly through the short-term interest rates and the industrial production channels. These findings are in strong conformity with those reported in previous empirical literature such in Cunado and Perez de Gracia (2014), Dhaoui et al. (2018a,b). Oil price acts, particularly, as an inflationary factor leading to high short-term interest rates and high operating costs. It constitutes also a factor of uncertainty and is therefore treated as a systematic risk which cannot be diversified but that must be priced.

5 Conclusion

Oil price fluctuations constitute a systematic asset price risk which induces a significant reaction in stock prices and returns. The impact of oil shocks on stock prices can be largely attributed to the impact of oil price shocks on both current and expected future real cash flows. Furthermore, oil price can also be considered as an inflationary factor stimulating an increase in operating costs and therefore an increase in prices. The reaction of real stock prices to the increase (decrease) in oil prices is attributed accordingly to the direct effects of this increase (decrease) in terms of cash flows and inflation. Oil price shocks lead to rising inflation and therefore depress macroeconomic growth and financial assets. In fact, the increase in oil price leads to a reduction in cash flow since oil constitutes a substantial input to production. In addition, changes in oil prices strongly impact the supply and demand for output, leading to low firm performance. This impact is explained by the fact that oil price changes directly affect the expected inflation rate and the real interest rate and consequently increase the discount rate for future cash flows.

This paper examines the predictive power of oil price shocks for stock prices in South Korea. We utilise a DCC, ADCC and GO-GARCH model to investigate the dynamic conditional correlations between oil prices (direct shock prices transmission), real industrial production and short-term interest rates (indirect transmission channels) on the one hand and the stock prices on the other hand. First, we find clear evidence of the long-run persistence of shocks in the three variables: oil prices, real industrial production and short-term interest rates. Our findings also show a negative dynamic conditional correlation between RSP and the real short-term interest rates and positive dynamic conditional correlation between RSP and Oil. Taken together, these results support the idea that oil price shocks play a pivotal role in increasing the systematic risk. The effect of oil price shocks is transmitted to stock markets through their impact on current and expected future real cash flows. Moreover, oil prices constitute an inflationary factor and therefore central banks are required to adjust their short-term interest rates in order to smooth the this inflationary effects on both real economy and financial activity. Finally, Oil price shocks are supposed to be treated as a systematic risk affecting the entire economy and consequently, must be hedged or priced as it is difficult to be managed by diversification.

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