The determinants of long-term correlation between crude oil and stock markets

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Abstract

This paper investigates the factors affect the long-term correlation between crude oil and stock markets by employing the DCC-MIDAS model and panel analysis. In the estimation of DCC-MIDAS, we find that the long-term conditional correlations between oil price and stock market prices are positive for all the cases expect during the time of global financial crisis in 2008 and European debt crisis in 2011.In the panel analysis, we find that the macroeconomic factors have significant impact on the long-term correlation between crude oil and stock markets. Specifically, the inflation has positive effect while GDP growth rate has negative effect. Our result can provide useful information to the investors and monetary authorities.

Keywords: Oil price, Stock market, GARCH-MIDAS, DCC-MIDAS

JEL classification: F3; G10

1. Introduction

The studies of comovements between crude oil and stock markets have important implications for energy policy and portfolio diversifications. Therefore, understanding the dynamic correlation between oil price and stock markets price is an important task not only for financial research but also for energy policy. After the study of Hamilton's (1983), there is a growing interest on the effects of oil prices on stock market returns and economy.

The studies of time-varying correlation have been well documented (Malik and Hammoudeh, 2007; Filis et al. , 2011; Arouri et al., 2012; Conrad et al., 2014; Basher and Sadorsky, 2016) as a risk manage tool in the portfolio management. Moreover, the financialization of commodity markets is strengthening as a result of a highly correlated market with the other financial markets, especially with stock market. The empirical evidences have recorded an increase of correlation between oil and stock market as well (Büyüksahin and Robe, 2014; Silvennoinen and Thorp, 2013). Given the links between oil and stock markets, it is our best interest to investigate the factors affecting the correlation between oil and stock markets. Though the correlation between oil and stock markets evolves with the time, we can draw out the long-term component in the time-varying correlation by the DCC-MIDAS model proposed by Colacito et al. (2011). Therefore, we can dig out the factors affect the long-term correlation between oil and stock markets

Our research can provide useful information for investors to allocate the portfolio or diversify internationally as we investigate the factors affect correlations between oil and stock markets. Since the correlations are keys for achieving the optimal portfolio, changes in correlations imply changes in portfolio weights. Specifically, our results show that the macroeconomic factors rather financial factors play an important role in determining the correlation between oil and stock markets. Moreover, the finding show that crude oil can reduce the risk of the portfolio during the financial crisis period as the correlation decreases.

This paper aims to investigate the determinants of long-term correlation between crude oil and stock markets by employing the DCC-MIDAS model proposed by Colacito et al. (2011). In addition, by implementing the panel analysis, we can detect the factors that can influence the dynamic conditional correlation between crude oil and stock markets in a comprehensive perspective.

Our contribution can be classified as threefold. Firstly, comparing other studies, we draw out the long-term component of volatility in the oil and stock markets. Secondly, we analyze the long-term component of time-varying correlation between oil and stock markets. Finally, we dig out the factors affecting the long-term component of time-varying correlation between oil and stock markets in a comprehensive perspective. The following sections of the paper are constructed by the literature review, methodology, data, empirical results, and conclusions.

2. Literature review

The academic studies have documented the amounting empirical evidence regarding the relationship between oil and stock markets. Generally speaking, the study on the relationship between crude oil and stock markets can be categorized into three types.

The first one is the causality relationship between crude oil and stock markets. Specifically, there are two different empirical results for that. In the one hand, the crude oil price movements have significant negative impact on stock market returns (Jones and Kaul, 1996;Sadorsky, 1999; Papapetrou, 2001; Kilian and Park, 2007; Hammoudeh and Li , 2005; Ghouri, 2006; Miller and Ratti, 2009; Aloui and Jammazi, 2009; Chen, 2010). All these studies find that the positive oil shock brings negative effect on the stock markets though they employ the different samples and countries. In the other hand, the relationship between crude oil market and stock market is positive and significant. For example, the evidence of a positive impact on the stock returns of oil and gas sectors in UK given an increase in oil price is provided by Chen et al. (1986), El-Sharif et al. (2005),Narayan and Narayan (2010), and Arouri and Rault (2011). In addition, other studies also show that an increased crude oil prices have a positive impact on stock prices in the emerging countries (Narayan and Narayan, 2010; Li et al., 2012; Zhu et al., 2014; Ghosh and Kanjilal, 2016).

In contrast to the first one, the second category can be classified by investigating dynamic correlation ship between oil and stock markets. Most of studies are based on the multivariate GARCH (MGARCH) model (Malik and Hammoudeh, 2007; Malik and Ewing, 2009; s. Arouri et al., 2011a; Arouri et al., 2011b; Filis et al. , 2011; Arouri et al., 2012; . Sadorsky, 2012; Sadorsky, 2014; Conrad et al., 2014; Basher and Sadorsky, 2016). For these papers, the aims are focusing on the volatility transmission and volatility spillover effect between crude oil and stock markets. For example, Filis et al. (2011) find that there is no significant difference in the time-varying correlation between oil price and stock prices for the oil-importing countries and the oil-exporting countries. Though there is no significant difference in the time-varying correlation between oil price and stock prices, a spillover effect from oil to stock markets in Europe and a bidirectional spillover effect between oil and US stock market sectors exist (Arouri et al.,2011a; Arouri et al., 2012). Conrad et al. (2014) provide the evidence that variables containing information on current and future economic activity are helpful predictors of changes in the oil–stock correlation. Moreover, Basher and Sadorsky (2016) provide an overview of time-varying correlation between crude oil market and emerging stock market and then estimate the hedging ratio.

The final type is other models used to investigate the dependence structure between crude oil and stock markets (Nguyen and Bhatti, 2012; Aloui et al, 2013; Martín-Barragán et al, 2015;Aloui and Aïssa, 2016). For most cases, this kind of investigations is based on the copula model or wavelet analysis. For example, Aloui et al, (2013) find a positive dependence between the oil and the stock markets of the six CEE countries. By employing wavelet approach, Martín-Barragán et al (2015) find the number of correlation breakdowns during oil shocks and stock market crashes is higher at low frequency with the detection of conation during the 2008 and 2011 stock market falls. Aloui and Aïssa (2016) also provide the evidence the dynamic of the relationship between oil price and stock price is not constant over time and its dependence structure is highly affected by the financial crisis and Great Recession.

In summary, while there are numerous literatures study causality relation between crude oil market and stock market, volatility spillovers between crude oil market and stock market, and dependence structure between crude oil market and stock market, there is little known about the factors determining the long-term correlation crude between oil market and stock market.

3. Methodology

To draw out the short- and long-term components of the dynamic correlation between oil price and stock market prices, we employ the DCC-MIDAS methodology proposed by Colacito et al. (2011). Assume there is a set of *n* asset with the vector of returns denoted by $\mathbf{r_t} = [r_{1,t}, ..., r_{n,t}]'$ and suppose it follows the following process:

$$r_t \sim i.i.d.N(\mu, H_t) \qquad H_t = D_t R_t D_t \tag{1}$$

where μ is the vector of unconditional means, H_t is the conditional covariance matrix and D_t is a diagonal matrix with standard deviations on the diagonal, and:

$$R_t = E_{t-1}[\xi\xi'] \qquad \xi = D_t^{-1}(r_t - \mu) \tag{2}$$

Particularly, we employ two step to estimate the model. In the first step, we estimate the conditional volatilities in D_t. In the second step, we estimate the conditional correlation matrix R_t.

3.1 GARCH-MIDAS component model

In this section, we estimate the short- and long-term components of volatility for each variables firstly based on the work of Engle et al. (2006). This class of models is refereed to be GARCH-MIDAS. Similar to the study of Engle and Rangel (2008), the GARCH-MIDAS also bases on mean-reverting unit daily GARCH process. Assume the univariate return for each asset $i = 1, ..., n$ follow the GARCH-MIDAS process:

$$r_{i,t} = \mu_i + \sqrt{m_{i,t} \cdot g_{i,t}}\xi_{i,t}, \forall t = \tau N_v^i, ..., (\tau + 1)N_v^i \tag{3}$$

where the short-run variance $g_{i,t}$ follows the a simple mean-reverting unit GARCH(1,1) process:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t-1} - \mu_i)^2}{m_{i,\tau}} + \beta_i g_{i,t-1} \tag{4}$$

with the restricted condition $\alpha_i > 0, \beta_i \geqslant 0$ and $\alpha_i + \beta_i < 1$. Particularly, we employ the daily to daily frequency to measure the short-run variance $g_{i,t}$.

The low frequency (MIDAS) component $m_{i,t}$ is a weighted sum of K_v^i lags of realized variances (*RV*) over a long horizon:

$$m_{i,\tau} = \bar{m}_i + \theta_i \sum_{i=1}^{K_v^i} \psi(\omega_v^i) RV_{i,\tau-1} \tag{5}$$

To ensure the covariance stationary process, the free parameter $\bar{m}_i$ and θ_i must satisfy the condition of $\bar{m}_i > 0$ and the $0 < \theta_i < 1$. Based on the study of Engle et al. (2006), the secular component $m_{i,\tau}$ relates to the effects of future expected global/macro-economic variables on volatility. Therefore, the realized variances (*RV*) involve N_v^i daily squared returns, namely:

$$RV_{i,\tau} = \sum_{j=(\tau-1)N_v^i+1}^{\tau N_v i} (r_{i,j})^2 \tag{6}$$

We set N_v^i equal to the number of trading days within a month and employ Beta weights to decay the parameter ω_v^i:

$$\psi_l(\omega_v^i) = \frac{(1-\frac{l}{K_v^i})^{\omega_v^i - 1}}{\sum_{j=1}^{K_v^i}(1-\frac{j}{K_v^i})^{\omega_v^i - 1}} \tag{7}$$

where the parameters N_v^i and K_v^i are independent of *i.i.e.* the same across all series. Obviously, the parameter ω_v^i and K_v^i determine the weight attached to past realized variances. For all $\omega_v^i > 1$, the weighting scheme $\psi_l(\omega_v^i)$ guarantees a decaying pattern while the rate of decay is determined by the size of ω_v^i. In other words, a rapidly decaying pattern comes with a large value of ω_v^i. Moreover, as the data drives the evolution process of $m_{i,\tau}$, the $m_{i,\tau}$ is expected to substantially differ across series though we apply a common parameter specification.

3.2 DCC–MIDAS dynamic correlation models

Following the study of Engle and Rangel (2008), we try to dig out the factors that can influence the DCC between oil price and exchange rate based on MIDAS polynomial since it is suitable to apply to lower frequency macroeconomic or financial variables. Therefore, we employ the DCC-MIDAS model introduced by Colacito et al. (2011) and is a natural extension of the GARCH-MIDAS model to the DCC model of Engle (2002). In this section, the dynamic correlations are calculated by the volatility adjusted (standardized) residuals $\xi_{i,t}$ obtained in previous section. Based on the results of section 3.1, it is possible to construct a matrix Q_t with its elements:

$$q_{i,j,t} = \bar{\rho}_{i,j,\tau}(1-a-b) + a\xi_{i,t-1}\xi_{j,t-1} + bq_{i,j,t} \tag{8}$$

$$\bar{\rho}_{ij,\tau} = \sum_{l=1}^{K_c^{ij}} \psi_l(\omega_r^{ij}) c_{i,j,t-l} \tag{9}$$

$$c_{i,j,t} = \frac{\sum_{k=t-N_c^ij}^{t} \xi_{i,k}\xi_{j,k}}{\sqrt{\sum_{k=t-N_c^ij}^{t} \xi_{i,k}^2}\sqrt{\sum_{k=t-N_c^ij}^{t} \xi_{j,k}^2}} \tag{10}$$

where *a* and *b* are the parameters driving the process of correlation with the stationary condition $a, b > 0$ and $a + b < 1$. Note the weighting scheme $\psi_l(\omega_r^{ij})$ is similar to Eq.(7). Particularly, the long-term correlation $\bar{\rho}_{i,j,\tau}$ is a weighted sum of span lengths of historical correlations K_c^{ij} lags of realized correlations daily calculated on the lag lengths N_c^{ij} non-overlapping returns. Hereafter, it is easy to use time varying covariances $q_{i,j,t}$ to calculate the daily conditional correlations between assets *i* and *j*:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}}\sqrt{q_{j,j,t}}} \tag{11}$$

Since $q_{i,j,t}$ is the short run correlation while $\bar{\rho}_{i,j,\tau}$ is a slowly moving long run correlation between assets *i* and *j*, we can rewrite Eq.(8) for easy interpretation:

$$q_{i,j,t} - \bar{\rho}_{i,j,\tau} = a(\xi_{i,t-1}\xi_{j,t-1} - \bar{\rho}_{i,j,\tau}) + b(q_{ij,t} - \bar{\rho}_{i,j,\tau})$$

which indicates the idea of short run fluctuations around a time-varying long run relationship. The structure of DCC-MIDAS model is similar to that of GARCH-MIDAS model. Instead of two components of volatility in GARCH-MIDAS model, there are two components of correlation in DCC-MIDAS model. One is the autoregressive structure of the classic dynamic conditional correlation $\rho_{i,j,t}$ to capture the short-term variations in correlation, another is slowly moving component $\bar{\rho}_{i,j,\tau}$ to reflect the fundamental or secular causes of time variation in correlation.

3.3 Estimation methodology

The parameters of the DCC-MIDAS model are estimated by the same two-step procedure of Engle (2002). In the first step, we estimate the parameters of univariate conditional volatility models with the vector $\Psi \equiv [\alpha_i, \beta_i, \omega_i, m_i, \theta_i, i = 1, ..., n]$. In the second step, we estimate the parameters of the conditional correlation model with the vector $\Xi = (a, b, \omega_r)$. Therefore, the following quasi-likelihood function is to be maximized:

$$QL(\Psi, \Xi) = QL_1(\Psi) + QL_2(\Psi, \Xi) \tag{12}$$

$$QL_1(\Psi) = -\sum_1^T (nlog(2\pi) + 2log(|D_t|) + \mathbf{r_t}' D_t^{-2} \mathbf{r_t}) \tag{13}$$

$$QL_2(\Psi, \Xi) = -\sum_1^T (log(R_t) + \xi_t' R_t \xi_t + \xi_t' \xi_t) \tag{14}$$

Therefore, the parameters of GARCH-MIDAS model are estimated in the first step, and the standardized residual are used to estimate the parameters of DCC-MIDAS model.

4. Data

There are two parts in our analysis. In the first step, we employ both the daily data for crude oil price and stock market price index to investigate the long-term correlation between oil and stock markets. . The WTI crude oil price is used to represent the crude oil price. The four major stock market price indexes are chosen, that is, TOPIX, EURO STOXX 50, FTSE 100, and S&P 500. The sample period is from Jan 3, 1994 to Dec 31, 2015 with the daily frequency. In all cases, the returns are calculated as one hundred times the first difference in the log of raw data. We illustrate the raw data in Fig. 1. The descriptive statistics for the returns are reported in Table 1. Table 1 summarizes the statistical properties of the log return of the crude oil and exchange rate. The results of the Jarque–Bera (J-B) test show that the null hypothesis of the normal distribution is rejected in all cases.

In the second part, we employ the monthly data of economic and financial variables for United Kingdom, Japan, EU, and US from Jan, 2005 to Dec, 2015. The definition of the variables is summarized in Table 4. For the choice of macroeconomic variables, we follows the previous literature of Bachmeier et al (2008) and Bachmeier and Cha (2011) by using the GDP growth rate and inflation rate. Based on the studies of Pyun and An (2016), Ferrer et al (2016), and Li (2016), we employ risk-free rate, credit risk in banking system, and term spread as the financial variables. Table 5 summarizes the descriptive statistics of these variables. All data are from DataStream.

5. Empirical results

5.1 Specifications of DCC-MIDAS model

In this section, we estimate the parameters of GARCH-MIDAS model firstly. The results are reported in Table 2. Almost parameters are significant at the 1% level except for the constant term. Specifically, the stationary condition is satisfied as $\alpha + \beta < 1$ for all the specifications implying the short-run volatility component is mean-reverting to the long-run trend. Moreover, the decay parameter ω is larger than one for all the returns. The results indicate a rather rapidly decreasing weighting function. The evolutions of conditional short- and long-term volatilities are plotted in Fig 2. As shown in Fig 2, there is a significant increase of volatility during the 2008 global financial crisis period for all the assets. Particularly, the Asian financial crisis in 1997 seems to have less impact on these markets than the global financial crisis did.

In the second step, we estimate the parameters of DCC-MIDAS model. Particularly, we set N_v^i equal to 21 in each month to obtain the monthly DCC between oil price and stock market prices. Moreover, we implement Fisher Z transformation to make ensure the DCC reflect the long-term conditional correlation between oil price and exchange rate precisely. The results are reported in Table 3. As shown in Table 3, Almost parameters are significant at the 1% level. In addition, the stationary conditions $a, b > 0$ and $a + b < 1$ are satisfied for all the specifications indicated in Table 3. The decay ω is larger than one for all the cases. In other words, the weight attached to past realized return variances decreases rapidly with the number of lags for the DCC-MIDAS model. Fig 3 plots the long-term component and total dynamic correlations between oil price and exchange rate.

According to Fig 3, we find that the dynamic correlations between oil price and stock market prices are positive except for the time when global financial crisis occurs. Our findings is consistent with the studies of Aloui and Jammazi (2009), Chen (2010), Aloui and Aïssa (2016), the global financial crisis significantly changes the daily dynamic correlations between oil and stock markets. Moreover, for the long-term correlations between oil and stock markets, there is a little effect from global financial crisis. As shown in Fig 3, there is a significant decrease of the long-term dynamic correlations during the global financial crisis in 2008 and European debt crisis in 2011, which indicates the crude oil can provide effective risk diversifications during the financial turmoil.

4.3 Identification of factors

In this section, we try to identify the factors that can influence the long-term dynamic correlations between oil price and stock market prices. Following the specifications in Table 4, we construct the following regression model:

$$cc = constant + \gamma_1 i + \gamma_2 g + \gamma_3 ts + \gamma_4 cr + \gamma_5 rf + \mu_i + v_{it} \quad (15)$$

For the economic variables, we choose annualized inflation rate and annualized GDP growth rate to reflect the current economic condition. There are three parts of the financial variables: risk-free rate, credit risk, and term spread. Specifically, risk-free rate denotes the price of a currency; credit risk denotes the credit premium required for a currency; term spread denotes the holding cost of a currency. The sum of these three variable denotes the cost of capital in this country. The definitions of these variables are summarized in Table 4.

The regression results are reported in Table 6. As shown in Table 6, we employ pool ordinary least square method as our base model. Based on the Hausman test, we employ the fixed effect model to run our regression instead of the random effect model. In addition, since the panel sample has four groups which much smaller than the time periods (100 month), it is reasonable to incorporate the time effect into the fixed effect model for further considerations. Therefore, the empirical results in model (3) show that both the GDP growth rate and risk-free rate have positive impact on the dynamic correlation while both inflation rate and credit risk have negative impact on the dynamic correlation. Mover, the model (4) and model (5) provide an additional evidence to support the estimation of model (3). However, the results from the model (4) and the model (5) seem not support the GDP growth rate as a factor.

To guarantee the robustness of our empirical results, we use autoregressive term of dynamic correlation as expansionary variable. The following regression model can be constructed:

$$cc = constant + cc(-1) + \gamma_1 i + \gamma_2 g + \gamma_3 ts + \gamma_4 cr + \gamma_5 rf + \mu_i + v_{it} \tag{16}$$

Similar to the Eq. (15), we employ fixed effect model based on the Hausman test. The empirical results in model (3) confirm that the inflation and GDP growth rate is an important factor in determining the dynamic correlation between crude oil and stock markets. Specially, the inflation has a positive effect while GDP growth rate has negative effect. However, the financial factors seem not the significant variables in determining the dynamic correlation. With the empirical results of model (4) and model (5), we can confirm inflation and GDP growth rate are important factors in determining the dynamic correlation between oil price and stock market prices.

It is easy to interpret the results as well. Based on the study of Bachmeier and Cha (2011), an increase of inflation rate will increase the nominal returns of both stock market and crude oil. Particularly, in our sample period, the inflation rate is modest. In addition, a relative strength of the economy will raise its stock market prices while decrease the returns of oil price relatively since the currency in this economy is appreciating (Basher et al, 2012).

Moreover, both Table 6 and 7 report the R^2, Adjusted R^2 and log likelihood for the comparison. We find that after incorporating the autoregressive term of dynamic correlation, all these statistics increase largely indicating the regression model with the autoregressive term performs better than that has not.

6. Conclusion

In this paper, we employ the GARCH-MIDAS model calculate the long-term volatility of crude oil and stock markets. We find that there is a significant increase of volatility during the 2008 global financial crisis period for all the assets. Particularly, the Asian financial crisis in 1997 seems to have less impact on these markets than the global financial crisis did. Moreover, by employing DCC-MIDAS model to investigate the long-term conditional correlation between oil and stock markets. Firstly, we find that the long-term conditional correlations between crude oil and stock markets are positive for all the cases expect during the time of global financial crisis in 2008 and European debt crisis in 2011. The findings are in line with the studies of Aloui and Jammazi (2009), Chen (2010), Aloui and Aïssa (2016). In addition, Japanese stock market prices show smallest degree of correlation with the oil price while UK’s stock market prices show largest degree.

Based on the panel analysis, we investigate the factors that can affect the long-term conditional correlation between crude oil and stock markets. We find that GDP growth rate has a negative effect while inflation has a positive effect on the long-term correlation between crude oil and stock markets. The empirical results indicate that a rise of inflation will increase the long-term conditional correlations between crude oil and stock markets while an increase of GDP growth rate will decrease long-term conditional correlations between crude oil and stock markets. The reason can be classified twofold. From the economic perspective, a rise of inflation in one country will increase nominal returns of both stock market prices and crude oil. Moreover, a relative strength of the economy will raise its stock market prices while decrease the returns of oil price relatively since the currency in this economy is appreciating.

There are at least two policy implementations to be considered. From the economic view, by identifying the inflation has positive impact on the relationship between oil price and stock market prices, we notice that the inflation environment plays an important role in the asset pricing. Therefore, the monetary authorities must take a care to implement monetary policy. In addition, the negative effect from the GDP growth rate, indicating exchange rate risk and contagion effect should be considered when the investors rebalance their portfolios. From the financial perspective, the diversification benefit exists between crude oil and stocks, especially during the financial crisis periods.

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Table 1. Descriptive statistics for the returns of oil price and stock market prices

	WTI	TOPIX	EURO 50	FSTE	S&P500
Mean	0.0168	0.0013	0.0144	0.0105	0.0257
Median	0.0000	0.0000	0.0299	0.0063	0.0288
Std	0.0237	0.0131	0.0140	0.0114	0.0116
Skewness	−0.1759	−0.269	−0.0531	−0.1632	−0.2469
Kurtosis	7.9511	9.2294	7.6989	9.1743	11.708
Correlation	1	0.0747	0.16014	0.1836	0.1537
Jarque-Bera	5891.576***	9349.003***	5282.556***	9141.575***	18195.04***
Obs	5739	5739	5739	5739	5739

Notes: Correlation indicates the correlation between oil price and exchange rate. *** indicates significant at the 1% level.

Table 2. The estimations of GARCH-MIDAS coefficients for the returns of oil price and stock market prices.

	WTI	TOPIX	EURO 50	FSTE	S&P500
	33.82	41.11	64.13	40.02	−52.17
$\mu \times 10^{-5}$	(27.76)	(15.82)***	(16.26)	(12.07)	(12.86)
	0.114	0.099	0.098	0.115	0.098
α	(0.009)***	(0.006)***	(0.006)***	(0.009)***	(0.006)***
	0.664	0.869	0.864	0.836	0.867
β	(0.031)***	(0.011)***	(0.012)***	(0.014)***	(0.012)***
	0.203	0.103	0.167	0.180	0.155
θ	(0.005)***	(0.028)***	(0.011)***	(0.010)***	(0.011)***
	23.21	4. 648	7.818	9.697	8.50
ω	(2.469)**	(2.236)**	(2.387)***	(2.354)**	(2.507)***
	9.561	11.81	8.871	6.040	7.594
$m \times 10^{-3}$	(0.750)***	(0.956)***	(0.751)***	(0.553)***	(0. 614)***
LL	11975.6	14896.6	14672.7	15902.4	15820.4
AIC	−23939.2	−29781.2	−29333.4	−31792.8	−31628.8
BIC	−23899.3	−29741.3	−29293.4	−31752.9	−31588.9

Notes: The number of MIDAS lags is 36 for the GARCH processes. The sample size is 5739 while the adjusted sample size is 4983 which covers Nov 26，1996 until DEC 31， 2015. *LL* refers to log likelihood ratio. The numbers in parentheses are standard errors.

*** indicates significant at the 1% level.

** indicates significant at the 5% level.

Table 3. The estimations of DCC-MIDAS coefficients between the returns of oil price and stock market prices.

	TOPIX	EURO 50	FSTE	S&P500
a	0.027 (0.013)***	0.032 (0.005)***	0.033 (0.007)***	0.038 (0.005)***
b	0.851 (0.078)***	0.946 (0.019)***	0.948 (0.018)***	0.943 (0.011)***
ω	7.853 (4.058)**	26.45 (12.58)**	25.13 (16.93)**	25.12 (12.42)**
LL	−6038.07	−5929.78	−5872.5	−5818.26
AIC	12082.1	11865.6	11751	11642.5
BIC	12102.1	11885.5	11771	11662.5

Notes: The number of MIDAS lags is 144 for the DCC processes. The sample size is 5739 while the adjusted sample size is 2139 which covers Aug 5，2005 until Dec 31，2015. *LL* refers to log likelihood ratio. The numbers in parentheses are standard errors.

*** indicates significant at the 1% level.

** indicates significant at the 5% level.

Table 4. Definition of variables

Name of the variables	Definition
Panel A: dependent variable:	
Conditional correlation (*cc*)	The conditional correlation is calculated by using the DCC-MIDAS model. We employ Fisher Z transformation (Colacito et al. 2011; Beine and Candelon 2011) to adjust for the potential problem of non-normality in the conditional correlation.
Panel B: dependent variable: Economic	
GDP growth (g)	GDP growth is annualized growth rate (%) of GDP in the country *n* based on the OECD composite leading indicator: Normalized GDP.
Inflation (*i*)	Inflation is annualized growth rate (%) of CPI in the country *n*.
Panel C: dependent variable: Financial	
Risk-free rate (*rf*)	Risk-free rate refers to the 3-month government bill yield in the country *n*.
Credit risk (*cr*)	Credit risk is calculated by the difference between 3-month interbank rate and the 3-month government bill yield in the country *n*. The variable measure the credit risk of banking system.

Term spread (*ts*)	Term spread is defined by the difference between long-term10-year government bond yield and the 3-month government bill yield in the country *n*.

Table 5. Summary statistics of variables

	cc	*g*	*i*	*rf*	*cr*	*ts*
Mean	0.2054	0.058	5.962	1.143	0.363	1.409
Std.	0.193	0.013	1.674	1.725	0.397	1.037
Maximum	0.193	4.558	4.543	6.059	3.185	3.757
Minimum	0.434	−7.083	−7.057	−0.561	−0.017	−0.995
Number of i.d.	4	4	4	4	4	4
Obs	500	500	500	500	500	500

Table 6. Estimation results for panel data analysis

cc	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Constant	0.046	0.186	0.299	0.207	0.286
	(0.018)***	(0.022)***	(0.021)***	(0.004)***	(0.023)***
g	0.058	0.055	0.018	0.006	
	(0.012)***	(0.011)***	(0.007)**	(0.007)	
$i \times 10^{-2}$	−0.053	−0.051	−0.033	−0.025	
	(0.012)***	(0.011)***	(0.006)***	(0.007)***	
rf	0.004	−0.039	0.048		−0.042
	(0.005)	(0.006)***	(0.007)***		(0.007)***
cr	−0.056	−0.049	−0.125		−0.132
	(0.019)***	(0.017)***	(0.013)***		(0.014)***
ts	0.123	0.058	0.005		0.012
	(0.009)***	(0.011)***	(0.009)		(0.011)
R^2	0.412	0.532	0.667	0.446	0.630
Adjusted R^2	0.406	0.525	0.661	0.441	0.625
LL	246.237	303.599	326.121	270.549	316.204
H test(5)			68.227***		

Notes: Model 1 is estimated by pool ordinary least square method. Model 2 is estimated by fix effect model. Model 3, 4 and 5 is estimated by fix effect model with time effect. The numbers in parentheses are standard errors. *LL* refers to log likelihood ratio. *H test* indicates Hausman test.

*** indicates significant at the 1% level.

** indicates significant at the 5% level.

Table 7. Estimation results for panel data analysis

cc	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Constant	−0.002	−0.002	0.002	0.007	0.010
	(0.002)	(0.004)	(0.008)	(0.002)***	(0.006)
cc(-1)	0.975	0.970	0.963	0.973	0.961
	(0.009)***	(0.011)***	(0.012)***	(0.010)***	(0.011)***
$g \times 10^{-2}$	−0.443	−0.412	−0.503	−0.571	
	(0. 257)	(0.257)	(0.217)**	(0.208)***	
$i \times 10^{-3}$	0.0033	0.032	0.034	0.041	
	(0.028)	(0.032)	(0.015)**	(0.018)***	
rf	0.001	0.001	−0.001		−0.002
	(0.011)	(0.002)	(0.002)		(0.003)
cr	0.005	0.005	−0.001		0.001
	(0.004)	(0.004)	(0.002)**		(0.004)
ts	0.004	0.003	0.002		0.001
	(0.002)	(0.002)	(0.003)		(0.003)
R^2	0.974	0.974	0.975	0.975	0.975
Adj R^2	0.973	0.973	0.975	0.975	0.974
LL	1021.077	1021.734	1023.775	1024.656	1020.114
H test(6)			54.452***		

Notes: Model 1 is estimated by pool ordinary least square method. Model 2 is estimated by fix effect model. Model 3,4 and 5 is estimated by fix effect model with time effect. The numbers in parentheses are standard errors. *LL* refers to log likelihood ratio. *H test* indicates Hausman test.

*** indicates significant at the 1% level.

** indicates significant at the 5% level.

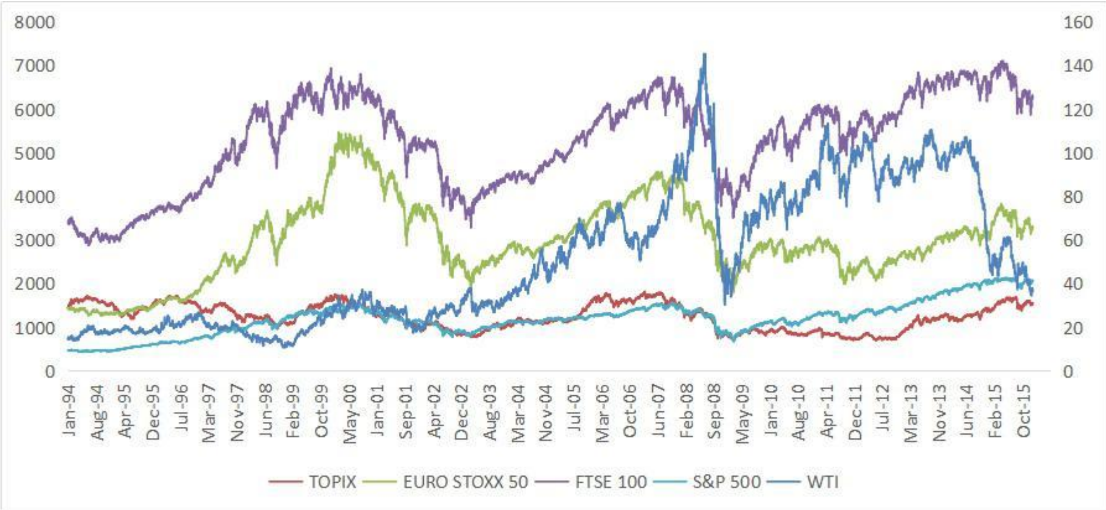
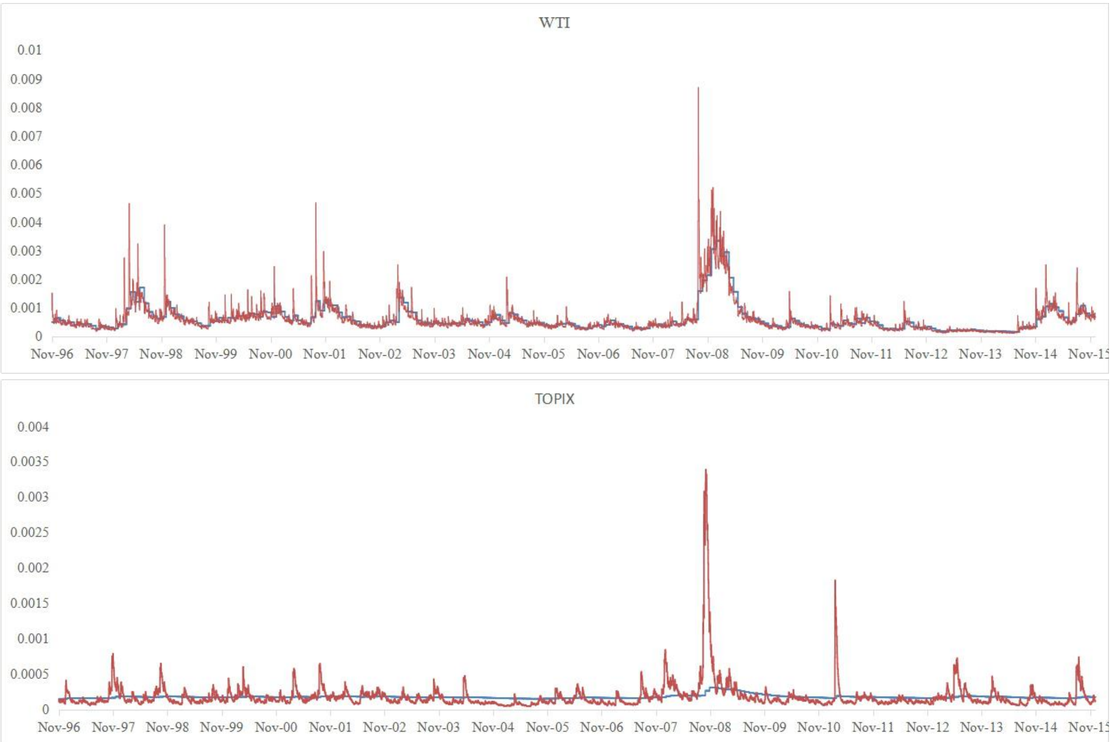


Fig 1. The plots of raw data. The left axis denotes the stock market prices index while the right axis denotes the crude oil price.



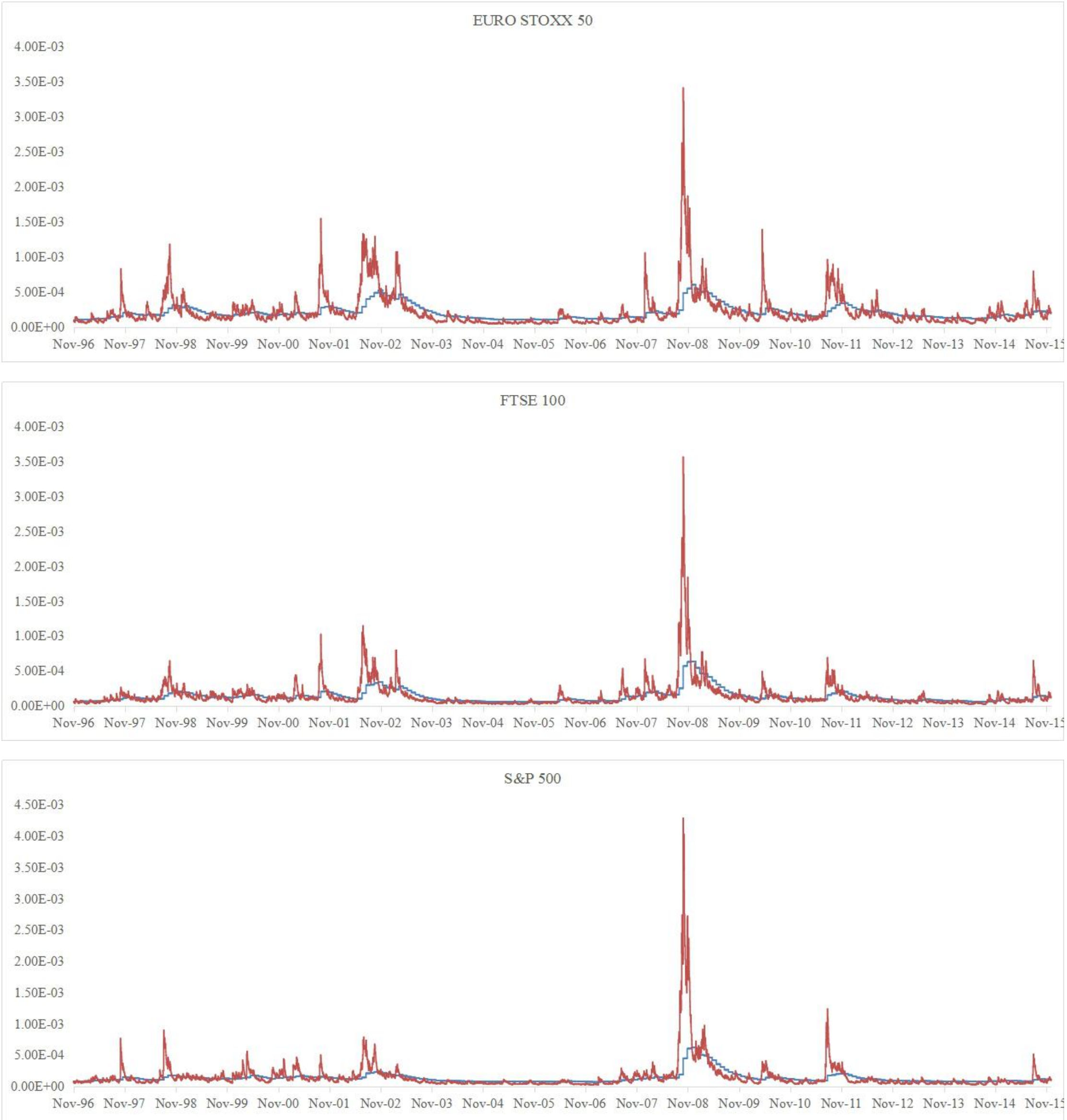
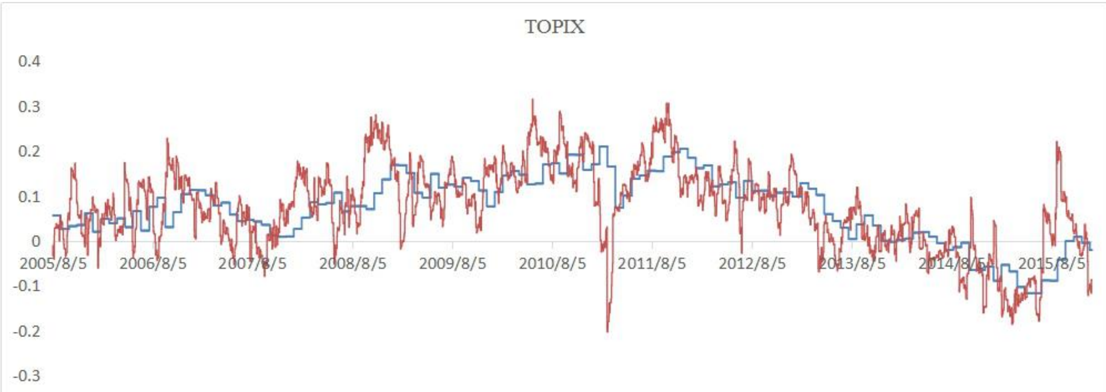


Fig. 2. The short and long term volatility for crude oil (WTI), TOPIX, EURO STOXX 50, FTSE 100, and S&P 500 respectively. The red line indicates the short term volatility while the black line indicates the long term volatility


TOPIX
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
2005/8/5
2006/8/5
2007/8/5
2008/8/5
2009/8/5
2010/8/5
2011/8/5
2012/8/5
2013/8/5
2014/8/5
2015/8/5


EURO STOXX 50
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
2005/8/5
2006/8/5
2007/8/5
2008/8/5
2009/8/5
2010/8/5
2011/8/5
2012/8/5
2013/8/5
2014/8/5
2015/8/5


FTSE 100
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
2005/8/5
2006/8/5
2007/8/5
2008/8/5
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2014/8/5
2015/8/5

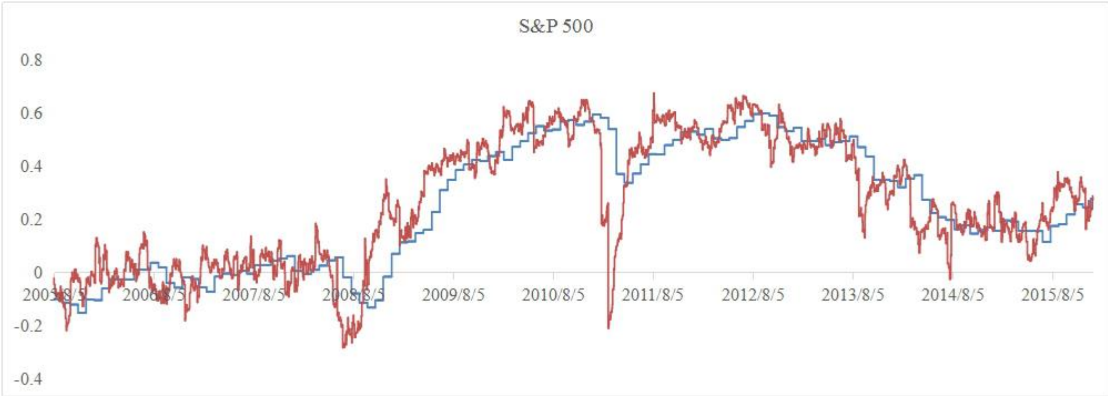

Fig. 3. The short and long DCC-MIDAS correlations between oil and stock market prices at the aggregated levels of four country groups, that is, TOPIX, EURO STOXX 50, FTSE 100, and S&P 500 respectively. The red line indicates the short term DCC while the black line indicates the long term DCC-MIDAS