The impact of oil price fluctuations on Greater China stock markets: Implication for portfolio management

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Abstract

Crude oil plays a pivotal role in modern economies. Stock markets, as a barometer of the state of our economy, are unlikely to escape the influence from oil market fluctuations. We investigate how and to what extent the information embedded in oil-price shocks is transmitted into stock markets in Greater China (China, Hong Kong and Taiwan). The focus of the research is on the volatility transmission between stock markets and oil markets within this region. We find that there is evidence of significant volatility transmission between oil and stock markets in Greater China at the sector-level, and that the intensity of volatility transmission varies across the stock sectors. These results imply that investors need to take into account additional source of uncertainty resulting from oil markets when investing in stock markets and should perhaps consider to incorporate oil assets into their portfolio designs to mitigate their investment risk. Our results are based on the VAR-GARCH framework with the DCC structure. The hedge effectiveness index indicates that this structure provides superior diversification benefits in terms of risk reduction when compared to the VAR-GARCH alternatives such as the CCC structure or the BEKK-structure.

Keywords: Oil prices; stock markets; Greater China; Portfolio management; VAR-GARCH model

1. Introduction

Financialization of energy market means that crude oil has become a recognized asset class within investment portfolios of financial institutions as a means to diversify risks such as inflation, and/or equity market weakness (see Gorton and Rowenhorst, 2006). This has resulted in increased inter-relationship between stock markets and oil prices. On the one hand, changes in the prices of oil, a key factor in the production process, affect financial performance or cash flows of firms, which in turn influence equity prices (e.g. Huang et al., 1996; Jones and Kaul, 1996). On the other hand, oil prices affect interest rates in the economy via inflation and monetary policy of the central bank, which in turn influence discount rate and equity prices (e.g. Apergis and Miller, 2009). Furthermore, the interaction between oil and stock markets does not dwell on the level of return variables, it also appears in volatility. Tauchen and Pitts (1983) and Ross (1989) suggest that it is the volatility of an asset rather than its return that is related to the rate of information flow in a market. This information flow is the pivotal point of risk management, asset pricing as well as its underlying derivatives pricing.

Despite the importance of information content embedded in the comovements of volatility between oil and stock markets, relatively little empirical work has been conducted on the extent of volatility transmission between oil and stock markets at the sector-level and such study may provide interesting insights into the nature of the volatility interaction between different asset classes.[2] Work has been carried out in the OECD countries to detect the impact of oil shocks on the stock markets of these largely oil-importing nations. To the best of our knowledge, no such study has been undertaken in the context of Greater China region (China, Hong Kong and Taiwan). This study tries to fill this gap by examining the information flow between oil and stock markets in Greater China region. It is important as Greater China, especially China, is considered a growth engine in the world and its stock markets are a very promising area for regional and global portfolio diversification. The impact of oil markets on stock markets and their sector-based stocks may have significant implications for investors. Furthermore, China is now the second largest oil

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[2] Much empirical literature has been devoted to the study of the impact of volatility shocks in crude oil markets on a variety of economic activities (e.g., Hamilton, 1983; Mork, 1989; Park and Ratti, 2008) and that the impacts are largely dissimilar across industries (e.g., Lee and Ni, 2002; Sadorsky, 2001; Boyer and Filion, 2007).

importer in the world and its economy is increasingly dependent on imported oil. Variations in economic growth or oil consumption may well be reflected in stock markets, then transmitted directly into oil prices (Li and Lin, 2011). Our results would have significant implications for oil users, traders, regulators and investors.

In this study we aim to examine the volatility and correlation interdependence between oil and stock markets in Greater China at the sector-level. This permits a greater understanding of pricing efficiency and information transmission via volatility flows among these interconnected markets. If there is a lack of significant inter-relationships across markets, then doubt may be cast on the efficiency of stock markets in Greater China in incorporating relevant information embedded in energy prices. Seven major types of industrial sectors are studied: Basic Materials, Consumer Goods, Consumer Services, Financials, Industrials, Technology, and Telecommunications sectors. Our consequential objective is to apply the estimated results to derive optimal portfolio weights and hedging ratios, which will effectuate optimal portfolio management in the presence of oil assets.

We employ the VAR-GARCH model proposed by Ling and McAleer (2003) to examine the volatility transmission between oil and stock markets (sectors) in Greater China. The ability of the VAR-GARCH model to capture cross-market volatility transmission has been empirically examined by recent research (see Arouri et al., 2011a; Chang et al., 2011). However, it has been noted that the constant conditional correlation assumption embedded into the VAR-GARCH model can be viewed as too restrictive as the correlation coefficient is likely to vary over time based on changes in economic and market situations. Therefore, we will assume the correlation part of the VAR-GARCH model follow the dynamic conditional correlation structure proposed by Engle (2002).

Using weekly data over the period from January 1, 2001 to October 31, 2011 for China, Hong Kong and Taiwan, we examine volatility transmission between seven industrial sectors and crude oils. The empirical results offer four major findings. First, there is evidence that the correlation between oil and stock markets (sectors) in Greater China is not constant but time-varying. It tends to increase with the volatility in the market. Second, there is significant transmission of shocks and volatility between oil and stock sectors. Third, the extent of volatility transmission varies across the seven stock sectors, which validates the argument that the sector perspective is more informative and generates more accurate implications for portfolio risk management. Finally, our analysis shows that stock market investors in Greater China should consider the additional source of uncertainty resulting from the strong connection between crude oil and stock markets in Greater China in terms of volatility transmission and then consider oil assets as a dynamic and valuable asset class that improves the risk-adjusted performance of a diversified portfolio of sector stocks.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 presents the data and describes the multivariate GARCH framework to be used in the analysis. Section 4 discusses the empirical results. Their implications on portfolio management in the presence of oil assets are shown in Section 5. Section 6 provides conclusions along with a few possible areas for future research.

2. Literature review

The relationship between oil price and macroeconomic variables are well documented in the literature through the studies on the impact of oil price changes on macroeconomic variables (Hamilton, 1983; Hooker, 1996; Kilian, 2008). The majority of these studies have found that rising oil prices and price volatility serve to stifle economic activity (Hamilton, 2003), whereas a reduction in oil prices does not necessarily lead to noticeable output growth (Mork, 1989; Mork and Olsen, 1994). Recently, the interconnection between oil price and stock markets has been added to the literature (Arouri, et al., 2011a; Jones and Kaul, 1996; Jones et al., 2004). These research aims to uncover the information flow between the two markets. Details analyses have been conducted to examine the relationship between sector indices and oil prices.

On the theoretical perspective, stock market returns and prices should reflect the effects of current and expected future impacts of oil price shocks (Jones et al., 2004). The study by Kaul and

Seyhun (1990) was the first to examine the reaction of stock markets to oil shocks. The authors consider the US stock market over 1949-1984 and report a detrimental effect of oil price shocks on the US stock market. Jones and Kaul (1996) propose a standard cash flow/dividends valuation model to examine stock markets efficiency in the US, Canada, Japan, and UK in terms of the degree to which stock prices changes in response to oil price changes. They find that the changes of oil price on the current and future cash-flows have a partially decisive effect on the four countries' real stock returns. Similar conclusion is also drawn in the Greek stock market as positive oil price shocks suppressed real stock returns (Papapetrou, 2001). As to oil-exporting countries, stock market prices are expected to be affected positively to oil price changes through positive income and wealth effects, which has been confirmed by Park and Ratti's (2008) findings that stock markets in Norway, an oil-exporting country, respond positively to oil price shocks.[3] Furthermore, as global economy shifts to emerging markets, the importance of the oil factor for stock prices is also discovered as Basher and Sadorsky (2006) suggest that emerging economies are more exposed to oil price shocks than more developed economies because they are less able to reduce oil consumption and thus more energy intensive, which causes significant changes in stock returns over both the short-run and long-run.

A number of studies have investigated the impact of oil price changes on the stocks of individual sectors, as it is important to know which sector indices are more sensitive to oil price fluctuations. A common belief is that oil price shocks are beneficial for oil-related companies (e.g. El-sharif et al., 2005; Boyer and Filion, 2007) and also have an impact on other sectors (e.g. Arouri and Nguyen, 2010; Arouri et al., 2011a). Recently, Elyasiani et al. (2011) examine the impact of changes in the oil returns and oil return volatilities on excess stock returns and return volatilities of thirteen US industries and show that oil fluctuations constitute a systematic asset price risk at the industry level as nine of the thirteen sectors analyzed show a statistically significant relationship between oil-futures return distribution and industry excess return. Surprisingly, the paper of Cong et al. (2008) shows that oil price shocks do not exert a statistically significant impact on the real stock returns of most Chinese stock market sectors indices, except for manufacturing index and some oil companies.[4]

More recently, the research emphasis has broadened to include not only the effects of changes in oil price level but also the effects of price volatility as well. The evidence confirms that oil volatility has a considerable influence on the stock market. For example, Malik and Ewing (2009) employ a bivariate GARCH model to detect volatility spillover between oil prices and five different US stock sector indexes, i.e. Financials, Industrials, Consumer Services, Health Care, and Technology. They find evidence of significant volatility transmission between oil prices and some of the examined market sectors. Arouri et al. (2011a) uses a VAR-GARCH (1, 1) model of Ling and McAleer (2003) to study the volatility transmission from oil prices to European equity markets. The authors show strong evidence of volatility spillover from oil to sector stock markets studied. Arouri et al. (2011b) also provides statistical support for the existence of volatility transmission between oil and stock markets in the Gulf Cooperation Council (GCC) countries over the period 2005 – 2010.

In summary, it can be stated that there are volatility spillovers between oil and stock markets, which have been tested in several countries. However, little is known about the volatility spillover effects between oil and stock markets in Greater China, which will be the focus of this paper. It also offers a new perspective on the literature on financial liberation and integration in Greater China, especially China, stock markets and international oil market.

3. Data and econometric method

3.1 Data descriptions

We use DataStream Global Country Indices to represent stock markets in China, Hong Kong and

[3] Jones and Kaul (1996) argue that the impact of oil price shocks to a country's economy of which reflected on stock returns are likely to vary across countries depending on their oil production and consumption level.

[4] Literature is abundant for the analysis of oil price effects on the stock market and the review here is brief and selective. We refer the reader to Kilian (2008) for detailed discussion.

Taiwan.[5] We also use DataStream Global Sector Indices to represent seven industrial sectors of stocks listed in China, Hong Kong and Taiwan, which includes Basic Materials, Consumer Goods, Consumer Services, Financials, Industrials, Technology, and Telecommunications. The use of sector data allows us to uncover relationships among individual sectors, hence equipping us better for making risk management and portfolio diversification decisions. All stock market data are extracted from DataStream International and all indices are expressed in local currencies.

We choose benchmark Brent crude oil futures prices, downloaded from DataStream International for our analyses. We choose Brent crude rather than WTI crude because that Brent crude is used to price two-thirds of the world's oil supply (Bloomberg, 2011)and that the ability of WTI in reflecting market conditions and its efficiency decreased sharply in recent years (Kao and Wan, 2011). In this study, we use front month future prices (the next contract to expire) because of the advantage of its liquidity, transparency, and flexibility in comparison to spot prices (Sadorsky, 2001). The latter (spot prices) are more heavily affected by temporary random noise than the futures prices. Finally, we convert Brent oil prices into local currency using US dollar exchange rates from DataStream International.

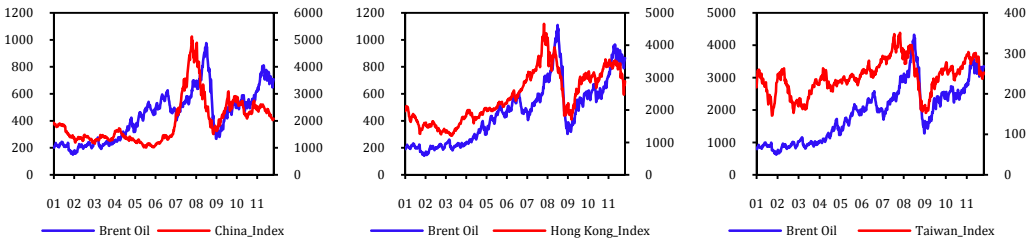

Fig.1 Dynamics of Brent oil prices (local currencies) and Market Indices in Greater China.

We employ weekly data over the period from January 1, 2001 through October 31, 2011. The choice of weekly frequency rather than daily frequency data enables us to avoid the possible problems such as day-of-the-week effects, the effects of illiquidity on asset prices, and non-synchronous trading in daily financial time series as well as the potential failure to capture the information content of changes in volatilities due to time aggregation and compensation effects.[6] The data contain 565 observations in each index. For our analysis, all weekly sample prices are converted into weekly nominal percentage returns. Log returns for both oil market and stock sectors are calculated and weekly variances are obtained by squared weekly returns.

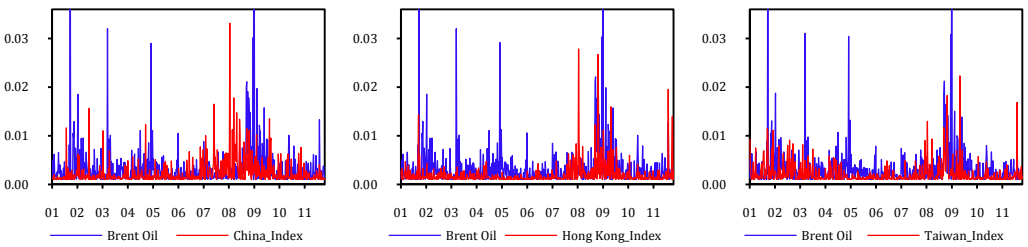

Fig.2 Dynamics of squared weekly returns for Brent oil (local currencies) and Market Indices in Greater China.

Plots of the raw data show that crude oil Brent and three stock markets in Greater China tend to move together (Fig.1[7]) over the period 2001-2011, suggesting they are contemporaneously correlated. We further plot the volatilities of Stock markets in Greater China against that of corresponding crude oil Brent in Fig. 2.[8] Several findings were obtained, which are presented as

[5] Please see http://thomsonreuters.com/content/financial/pdf/i_and_a/indices/datastream_global_equity_manual.pdf for detailed indices construction.

[6] Very recently, it has been empirically shown that weekly data is superior to daily or monthly data when being employed to examine the oil-stock market relationships with respect to in-sample estimation and out-of-sample forecast (Arouri and Nguyen, 2010).

[7] Due to space limitation, the sector indices in Greater China are not included in this paper. The patterns are similar and are available from the authors on request.

[8] See footnote 7.

follows. (1) As an emerging market, the Chinese stock market is more volatile than the mature Hong Kong and Taiwan markets, which is consistent with many studies on the Chinese stock market (e.g., Lin et al., 2009). (2) The volatilities of Stock markets in Greater China have relatively synchronized fluctuations with the Brent oil market; this is especially true for the Hong Kong market. (3) Volatility spikes occurred in all three stock markets in October 2008 following the collapse of Lehman Brothers. However, the volatility of the Brent oil market reached its climax only two months later, significantly dwarfing the volatilities of Greater China stock markets. These general patterns clearly indicate the potential of volatility spillover between oil and stock markets in Greater China.

Table 1
Summary statistics for daily returns.

China	Mean (%)	Std. Dev. (%)	Skew.	Kurt.	JB	ARCH(20)	Q(20)	Corr. with oil
Brent	0.22	4.84	-0.41	5.46	158.4^{+++}	4.98^{+++}	24.1^{+++}	1.00
Market Index	0.01	3.78	-0.31	4.51	62.3^{+++}	4.24^{+++}	63.2^{+++}	0.12
Basic Materials	0.07	4.83	-0.28	4.68	74.1^{+++}	5.81^{+++}	55.7^{+++}	0.16
Consumer Goods	0.12	4.21	-0.32	5.04	107.3^{+++}	4.03^{+++}	65.5^{+++}	0.03
Consumer Services	0.10	4.47	-0.65	5.73	214.1^{+++}	7.29^{+++}	73.6^{+++}	0.04
Financials	0.03	4.09	-0.03	4.53	55.0^{+++}	2.41^{+++}	37.9^{+++}	0.09
Industrials	-0.18	4.30	-0.48	4.89	105.5^{+++}	4.75^{+++}	56.6^{+++}	0.07
Technology	-0.02	4.63	-0.54	4.88	110.4^{+++}	3.24^{+++}	26.9	0.07
Telecommunications	-0.15	5.84	-0.24	4.53	60.4^{+++}	2.92^{+++}	32.5^{+++}	0.08
Hong Kong	**Mean (%)**	**Std. Dev. (%)**	**Skew.**	**Kurt**	**JB**	**ARCH(20)**	**Q(20)**	**Corr. with oil**
Brent	0.27	4.85	-0.43	5.46	159.9^{+++}	5.08^{+++}	25.0	1.00
Market Index	0.07	3.31	-0.52	6.36	291.1^{+++}	5.75^{+++}	35.9^{++}	0.32
Basic Materials	0.02	4.94	-0.72	9.53	1049.8^{+++}	11.48^{+++}	29.6^{+}	0.31
Consumer Goods	0.24	3.88	-0.34	6.03	225.9^{+++}	5.26^{+++}	26.4	0.15
Consumer Services	0.13	3.64	-0.63	8.83	837.2^{+++}	6.58^{+++}	29.4^{+}	0.26
Financials	0.01	3.42	-0.33	7.14	413.6^{+++}	6.23^{+++}	38.0^{+++}	0.31
Industrials	0.02	3.83	-0.52	7.33	465.9^{+++}	4.42^{+++}	23.9	0.29
Technology	0.09	4.90	-0.29	4.46	57.5^{+++}	2.69^{+++}	39.8^{+++}	0.22
Telecommunications	0.07	4.38	-0.34	4.24	47.2^{+++}	4.02^{+++}	25.2	0.20
Taiwan	**Mean (%)**	**Std. Dev. (%)**	**Skew.**	**Kurt**	**JB**	**ARCH(20)**	**Q(20)**	**Corr. with oil**
Brent	0.25	4.76	-0.39	5.74	190.7^{+++}	4.31^{+++}	24.1	1.00
Market Index	0.28	3.49	-0.23	4.37	49.3^{+++}	4.47^{+++}	30.4^{+}	0.18
Basic Materials	0.20	3.76	-0.31	5.78	189.8^{+++}	2.46^{+++}	23.9	0.18
Consumer Goods	0.12	4.25	-0.37	4.69	80.4^{+++}	2.86^{+++}	16.4	0.11
Consumer Services	-0.03	3.88	0.05	5.97	207.3^{+++}	4.71^{+++}	21.4	0.06
Financials	0.01	4.09	0.20	5.71	176.8^{+++}	3.88^{+++}	17.9	0.15
Industrials	0.02	4.45	-0.26	4.72	75.6^{+++}	2.07^{+++}	28.2	0.13
Technology	-0.02	4.39	-0.29	4.03	32.9^{+++}	5.93^{+++}	36.8^{+}	0.16
Telecommunications	0.03	2.46	-0.79	7.09	452.8^{+++}	4.56^{+++}	19.5	0.13

Notes: This table reports the basic statistics of return series of oil and stock sectors indices, including mean (Mean), standard deviation (Std. Dev), skewness (Skew.), kurtosis (Kurt.), and correlation between stock sectors and crude oil Brent (Corr. with oil). JB, ARCH(20), and Q(20) refer to the empirical statistics of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 20, and the Ljung-Box (1978) tests for autocorrelations of order 20 applied to standardized residuals in levels. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5%, and 1% levels respectively.

The summary statistics for the return series are shown in Table 1. It is clear that the means of the return series are relatively small compared to the corresponding standard deviations. On average, Brent oil market realized higher returns than corresponding stock markets (sectors) in Greater China over our sample period, except for Taiwan market index. The negative skewness in most cases and higher kurtosis lead up to the rejection of the normality assumptions for returns distributions, which is corroborated by the Jarque-Bera (1980) test at the significance level of 1%. Engle's ARCH test (1982) indicates the existence of heteroscedasticity for all return series at the 1% level. The Ljung-Box (1978) Q statistic on the returns series indicates strong autocorrelation up to 20th order in China market and weak autocorrelation up to 20th order in Hong Kong and Taiwan markets in general. Unconditional correlations between oil and stock markets (sectors) in Greater

China show that there are weak positive correlations on average with the highest correlation (0.32) observed in the Hong Kong market index and the lowest correlation (0.03) observed in the Consumer Goods sector in China market.[9]

3.2 Multivariate conditional volatility models

Multivariate GARCH (MGARCH) models have been commonly used to estimate the volatility spillover effects among different markets. Andersen et al. (1999) show that MGARCH models perform well relative to competing alternatives.[10] Especially, MGARCH models have been used in the energy economics and finance literature to study oil prices (see Chang et al., 2010, 2011), and to study volatility transmissions in equity markets (see Khan and Batteau, 2011).

In this paper, we use the VAR-GARCH (1, 1) model, introduced by Ling and McAleer (2003), to investigate volatility transmission between Brent oil and sector stock prices in Greater China. This model will also enable us to determine the optimal weights and optimal hedging ratios for oil-stock portfolio holdings.[11] The ability of the VAR-GARCH (1, 1) specification to capture cross-market volatility transmission has been empirically examined by recent research (Arouri et al., 2011b; Chang et al., 2011). Applying this model to our research, the variables of interest are modelled as a vector process containing a deterministic part and a stochastic part. More specifically, the weekly vector time series R_t is modelled as follows:

$$\begin{aligned} R_t &= \mu + \Phi R_{t-1} + \varepsilon_t\,, \quad \varepsilon_t | I_{t-1} \sim N(0, H_t) \\ \varepsilon_t &= \eta_t H_t^{1/2} \end{aligned} \tag{1}$$

where $R_t = (r_t^O, r_t^S)'$ is the vector of the returns on Brent oil price and stock sector indices in Greater China respectively, $\mu = (\mu^O, \mu^S)'$ is the deterministic vector specifying the unconditional means of R_t and $R_{t-1} = (r_{t-1}^O, r_{t-1}^S)'$ is used to model the interdependence between oil and stock sector return series, $\varepsilon_t = (\varepsilon_t^O, \varepsilon_t^S)'$ is the stochastic vector specifying the random error term of the mean equation for the returns on Brent oil price and stock sector indices in Greater China respectively, $\eta_t = (\eta_t^O, \eta_t^S)'$ is a sequence of independently and identically distributed (i.i.d.) random vectors. The market information available at time $t-1$ is denoted as I_{t-1}, and $H_t = \begin{bmatrix} h_t^O & h_t^{OS} \\ h_t^{SO} & h_t^S \end{bmatrix}$ is the matrix of conditional variances of oil and stock returns with h_t^O and h_t^S being specified as:

$$\begin{aligned} h_t^O &= c_O^2 + a_{O1}^2(\varepsilon_{t-1}^O)^2 + a_{O2}^2(\varepsilon_{t-1}^S)^2 + \beta_{O1}^2 h_{t-1}^O + \beta_{O2}^2 h_{t-1}^S \\ h_t^S &= c_S^2 + a_{S1}^2(\varepsilon_{t-1}^O)^2 + a_{S2}^2(\varepsilon_{t-1}^S)^2 + \beta_{S1}^2 h_{t-1}^O + \beta_{S2}^2 h_{t-1}^S \end{aligned} \tag{2}$$

This equation facilitates large shocks to one variable to directly affect the variance of another variable through the cross values of error terms, $(\varepsilon_{t-1}^O)^2$ and $(\varepsilon_{t-1}^S)^2$, as well as those of lagged conditional volatilities, h_{t-1}^O and h_{t-1}^S, which depict the extent to which current levels of the conditional variance are related to past conditional variance (see Ling and McAleer, 2003).

With regard to the conditional correlation between Brent oil and sector stocks in Greater China, one way to model it is to apply Engle's (2002) dynamic conditional correlation (DCC) structure. In the DCC structure, the variance-covariance matrix H_t is assumed as:

$$H_t = diag\left(\sqrt{h_t^O}, \sqrt{h_t^S}\right) P_t diag\left(\sqrt{h_t^O}, \sqrt{h_t^S}\right) \tag{3}$$

in which the conditional correlation matrix P_t is given as:

[9] The weak positive correlation between stock and oil market is also observed in the Europe and Gulf Cooperation Council (GCC) countries. Arouri et al. (2011a) suggest that this is due to the implication that oil price increases over the last decade were seen as indicative of higher expected economic growth and then corporate earnings.

[10] For example the continuous stochastic diffusion models.

[11] Similar to previous studies, one lag is included in the conditional variance equation (Eq. 2). Recently examples of VAR-GARCH (1, 1) approach include Chang et al. (2010), Hammoudeh et al. (2009).

$$P_t = [diag(\sqrt{q_{11,t}}, \sqrt{q_{22,t}})]^{-1} Q_t [diag(\sqrt{q_{11,t}}, \sqrt{q_{22,t}})]^{-1} \quad (4)$$

where $Q_t = (q_{ij,t})$ is a 2x2 symmetric positive definite matrix given by:

$$Q_t = [1 - \theta_1 - \theta_2]\overline{Q} + \theta_1 \xi_{t-1} \xi'_{t-1} + \theta_2 Q_{t-1} \quad (5)$$

where θ_1 is a positive and θ_2 a non-negative scalar parameter to capture the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation respectively. Their sum is less than unity to ensure the positive definite of the variance-covariance matrix H_t. $\overline{Q}$ is the 2x2 unconditional correlation matrix of the standardized residuals ξ_{t-1}.[12] The correlation estimator is given as $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t} q_{jj,t}}$. Engle (2002) presents the conditional correlation as a weighted sum of past correlations. For the DCC structure, the null hypothesis of $\theta_1 = \theta_2 = 0$ is tested to determine whether imposing constant correlations is relevant. The disadvantage of the DCC specification is that θ_1 and θ_2 are scalars, therefore, the conditional correlations feature the same dynamics. This is a necessary condition to ensure P_t is positive definite for all *t.*

Alternatively, we can assume the correlations to be constant to ease the burden of estimation and inference procedure by considering Bollerslev's (1990) constant conditional correlation (CCC) structure given by:

$$H_t = diag\left(\sqrt{h_t^O}, \sqrt{h_t^S}\right) \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} diag\left(\sqrt{h_t^O}, \sqrt{h_t^S}\right) \quad (6)$$

where ρ denotes the correlation coefficient between ε_t^O and ε_t^S and assumes to be constant over time. The CCC structure has been introduced because of its computational simplicity (Lien and Tse, 2000). The conditional covariance between sector indices and oil returns is modelled as:

$$h_t^{OS} = h_t^{SO} = \rho \sqrt{h_t^O h_t^S} \quad (7)$$

Although the VAR-GARCH (1, 1) model with CCC structure performs quite well in modelling of volatility transmission, empirical studies have suggested that the assumption of constant conditional correlations may be too restrictive given changing economic conditions, thereby entailing the need to incorporate time-varying correlations (see Chang et al., 2010).

The VAR-GARCH (1, 1) model with DCC or CCC structure are computationally simpler and may be estimated consistently in two steps based on the likelihood function, the first step being a series of univariate GARCH estimates and the second step being the correlation estimates based on the standardized residuals from step one.

An alternative dynamic conditional correlation model featuring volatility transmission effects is the BEKK model of Engle and Kroner (1995), which need not to impose restrictions on the parameters to guarantee the positive definite of H_t. The BEKK model for multivariate GARCH (1, 1) is given as:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \quad (8)$$

where C is a lower triangular matrix and A and B are 2x2 parameter matrices. Matrix A measures the extent to which conditional variances are correlated with past squared unexpected returns and consequently the effects of shocks on volatility. At the same time, matrix B depicts the extent to which current level of conditional variance-covariance matrix is related to past conditional variance-covariance matrices. The disadvantage of the BEKK model is that it is computationally complicated and the estimated coefficients for the variance-covariance matrix cannot be interpreted on an individual basis (see Caporin and McAleer, 2009).

In what follows in next section we apply the VAR-GARCH (1, 1) model with DCC structure to

[12] The standardized residuals ξ'_t is defined as $\xi'_t = \varepsilon'_t[diag(\sqrt{h_t^O}, \sqrt{h_t^S})]^{-1}$; the unconditional correlation matrix $\overline{Q}$ is defined as $\overline{Q} = T^{-1}\sum_{t=1}^{T} \varepsilon_t \varepsilon'_t$.

model the volatility dynamics between oil and stock markets in Greater China, and the VAR-GARCH (1, 1) model with CCC structure and the BEKK-GARCH (1, 1) model are used especially to compare the results of diversification and hedging effectiveness. All three models are estimated by Quasi-Maximum Likelihood estimation (QMLE) with robust standard errors using the BFGS algorithm.[13]

4. Empirical results

The estimation results of the VAR-GARCH model with DCC structure are reported in Table 2, 3 and 4 for the bi-variable modelling of oil and stock (sector) returns in Greater China.[14]

The results show that the volatility sensitivity to own lagged conditional volatility (GARCH terms) is significant for all oil and stock return series at the 1% level. Moreover, changes in the current conditional volatility of both oil and stock returns, except for Industrials sector in China, also depend on their own lagged shocks (ARCH terms), which are indicated by the significance of the estimates of ARCH coefficients at conventional levels. The degree of shock dependence in the short run varies across different stock markets with the shock dependence in China stock market is the lowest, followed by Taiwan and Hong Kong stock markets. In terms of volatility persistence in the long run, China stock market is the highest, followed by Hong Kong and Taiwan stock markets. This signifies that convergence to the long-run equilibrium due to a shock in the volatility series is slower in China than in Hong Kong and Taiwan. Furthermore, the larger magnitude of GARCH-term estimates, combined with the smaller size of ARCH-term estimates, indicates gradual fluctuations of conditional volatility over time for China, Hong Kong and Taiwan stock markets, which suggests that investors participating in oil and stock markets in Greater China may consider active asset management strategies based on volatility persistence and current market trends.

After the analyses of the volatility pattern of oil and stock markets based on their own past information, we now turn our attention to the extent of volatility transmission between oil and stock markets. Details of the volatility transmission between oil and stock markets are discussed in section 4.1. Section 4.2 will examine the volatility transmission between oil and sector indices. The dynamic conditional correlations are analyzed in section 4.3.

4. 1 Volatility transmissions: the country-level perspective

From Table 2 to 4, we observe that the conditional volatility of the China-wide stock market, represented by the DataStream Country Index (China), is affected by innovations and past volatility of the oil market as indicated by the significance at the 1% level of the coefficients on $(\varepsilon_{t-1}^{O})^2$ and h_{t-1}^{O} respectively. A shock originating from the oil market leads to decrease China stock market volatility. Similarly, the gradual fluctuation of conditional volatility over time in the oil market also results in the decrease in China stock market volatility. On the other hand, past China stock market shocks and volatility are found to drive volatility up in the oil market, which are verified by the positive significance of the coefficients of $(\varepsilon_{t-1}^{S})^2$ and h_{t-1}^{S} in the conditional volatility equation for oil returns. In Hong Kong stock market, only oil's past volatility, represented by h_{t-1}^{O}, has significant and positive effect on its stock market, but not the other around. While in Taiwan stock market, there is no evidence to suggest that there are cross effects of conditional volatility between oil markets and stock market in any direction.

[13] The QMLE will make sure the robustness of the estimation to any departure from normality conditions (Ling and McAleer, 2003) and all computations are carried out using WinRATS 8.0.

[14] The other three models are also estimated, but the results are not shown here as they are used especially to compare the results of diversification and hedging effectiveness. The estimation results are available from the author upon request. As the one-period lagged returns in the mean equation were not statistically significant, only constant terms are included in Eq. (1) for the parameter estimations.

Table 2
Estimates of VARMA-GARCH(1,1) model with DCC structure for oil and stock sectors in China

Variables	Market Index		Basic Materials		Consumer goods		Consumer services		Financials		Industrials		Technology		Telecommunications	
	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock
Conditional mean equation																
Constant	0.0039**	0.0004	0.0038**	-0.0001	0.0037**	0.0003	0.0040***	0.0007	0.0040***	0.0003	0.0029	-0.0027	0.0043***	0.00004	0.0030*	-0.0017
Conditional variance equation																
Constant	0.0001***	0.0001***	0.0002***	0.0002***	0.0002***	0.00001***	0.0001***	0.00004***	0.0002***	-2.4E-6***	0.0002**	-0.00003	0.00007***	0.00003***	0.0002***	0.0001***
$(\varepsilon_{t-1}^{O})^2$	0.0503***	−0.0277***	0.0714***	−0.0298***	0.0833***	−0.0847***	0.0671***	−0.0442***	0.0583***	−0.0068***	0.0805***	−0.1231**	0.0620***	−0.0316***	0.0736***	0.0613***
$(\varepsilon_{t-1}^{S})^2$	0.0252**	0.0063***	0.0252	0.0484***	0.1039***	0.0182***	0.0467***	−0.0017***	0.0284***	0.0025***	0.0607	0.0624	0.0588***	−0.0008***	0.0617***	0.0372***
h_{t-1}^{O}	0.8468***	−0.3079***	0.8584***	−0.0439***	0.8517***	0.2711***	0.8364***	−1.4543***	0.8105***	−0.2263***	0.8592***	1.1886**	0.8301***	−0.6456***	0.8829***	−0.4732***
h_{t-1}^{S}	0.6076***	1.0315***	-0.0352	0.9549***	−0.6445***	0.9711***	1.1786***	1.0384***	0.7322***	1.0214***	−0.7627**	0.8759***	0.9758***	1.0360***	−0.4164***	0.9566***
Dynamic Conditional Correlation (DCC)																
θ_1	0.0106***		0.0496		0.0965***		6.1E-8		0.0093***		0.0969***		0.00004		0.0338***	
θ_2	0.0001		0.0001		0.2028		1.4E-6		0.8846***		0.0000		0.00000		0.8328***	
Average DCC	0.1223		0.1631		0.0288		0.0401		0.0888		0.0706		0.0747		0.0756	
Diagnostic statistics																
Log L	2037.6		1916.9		1974.2		1971.7		1971.1		1958.5		1916.1		1759.2	
JB	145.1+++	15.95+++	143.9+++	31.02+++	115.6+++	12.06+++	136.4+++	6.827+++	144.6+++	37.54+++	93.34+++	58.00+++	131.2+++	25.37+++	102.3+++	66.37+++
ARCH(20)	0.6038	0.6948	0.6525	1.2397	0.6403	0.6141	0.5942	0.7453	0.6901	0.4508	0.7531	0.4593	0.5908	0.7162	0.6967	1.1020
Q(20)	11.309	28.900+	11.519	24.650	11.251	36.528++	11.106	25.593	10.674	23.626	11.227	27.966	11.190	15.071	10.887	24.370
$Q^2(20)$	12.252	14.440	13.526	27.377	13.214	14.055	12.266	17.762	14.095	9.487	15.797	10.211	12.118	14.163	14.515	23.765

Notes: Oil and stock are oil price returns, stock sector index returns respectively. *, **, and *** indicate significance at the 10%, 5% and 1% respectively. Model is estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. The Log L (Log Likelihood) criterion measures the relative goodness of fit of the estimated model. JB, ARCH(20), Q(20), and $Q^2(20)$ refer to the empirical statistics of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 20, and the Ljung-Box (1978) tests for autocorrelations of order 20 applied to standardized residuals in levels and squared standardized residuals respectively. +, ++, and +++ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5%, and 1% levels respectively.

Table 3
Estimates of VARMA-GARCH(1,1) model with DCC structure for oil and stock sectors in Hong Kong

Variables	Market Index		Basic Materials		Consumer goods		Consumer services		Financials		Industrials		Technology		Telecommunications	
	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock
Conditional mean equation																
Constant	0.0044***	0.0023**	0.0043***	0.0016	0.0043**	0.0044***	0.0034***	0.0037***	0.0046***	0.0019*	0.0041**	0.0020	0.0035**	0.0029	0.0041**	0.0015
Conditional variance equation																
Constant	0.0001***	0.00004***	0.0002***	0.0001***	0.0001***	0.0002***	-0.00005^{***}	0.00008***	0.0001***	0.0001***	0.0002***	0.0001***	0.0001***	0.0001***	0.0002***	0.00005***
$(\varepsilon_{t-1}^{O})^2$	0.0727***	-0.0108	0.0695***	-0.0562^{*}	0.0773***	0.0156	-0.0366^{***}	-0.0432^{***}	0.0747***	-0.0187^{*}	0.0751***	0.0153	0.0740***	-0.0043	0.0751***	0.0421***
$(\varepsilon_{t-1}^{S})^2$	-0.0056	0.1374***	0.0132	0.1947***	-0.0147	0.2433***	-0.0629^{***}	0.2075***	-0.0185	0.1603***	-0.0068	0.1479***	-0.0110	0.0917***	-0.0094	0.0727***
h_{t-1}^{O}	0.8659***	0.0629***	0.8599***	0.1734***	0.8608***	0.0568	0.8879***	0.3490***	0.8726***	0.1458***	0.8593***	0.0926***	0.8644***	0.0447*	0.8357***	-0.0627^{***}
h_{t-1}^{S}	-0.0095	0.8093***	-0.0064	0.7439***	-0.0380	0.6361***	1.0134***	0.6270***	-0.0201	0.7470***	-0.0009	0.7885***	-0.0120	0.8711***	0.0922**	0.9067***
Dynamic Conditional Correlation (DCC)																
θ_1	0.0285***		0.0379***		0.0182***		0.0048***		0.0280***		0.0247***		0.0216***		0.0166***	
θ_2	0.9713***		0.9616***		0.9797***		0.7722***		0.9720***		0.9749***		0.9763***		0.9817***	
Average DCC	0.2116		0.1888		0.1077		0.2569		0.1851		0.1988		0.1681		0.1468	
Diagnostic statistics																
Log L	2171.1		1997.7		2032.7		2103.8		2175.6		2069.9		1884.4		1958.4	
JB	147.6^{+++}	62.85^{+++}	154.0^{+++}	148.7^{+++}	140.7^{+++}	28.73^{+++}	14.95^{+++}	102.4^{+++}	141.1^{+++}	75.53^{+++}	149.6^{+++}	103.2^{+++}	142.3^{+++}	14.43^{+++}	136.0^{+++}	30.54^{+++}
ARCH(20)	0.6244	0.7165	0.6180	0.4590	0.5968	0.7276	1.0789	1.3537	0.6153	0.6302	0.6208	0.6560	0.6395	0.7143	0.6186	0.4515
Q(20)	11.591	21.679	11.531	23.647	11.529	23.452	14.493	20.007	11.607	20.785	11.559	22.307	11.688	31.016^{+}	11.318	19.853
$Q^2(20)$	12.979	12.859	12.827	8.438	12.467	14.558	21.947	21.436	12.720	10.662	12.944	11.467	13.256	13.026	13.062	8.334

Notes: Oil and stock are oil price returns, stock sector index returns respectively. *, **, and *** indicate significance at the 10%, 5% and 1% respectively. Model is estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. The Log L (Log Likelihood) criterion measures the relative goodness of fit of the estimated model. JB, ARCH(20), Q(20), and $Q^2(20)$ refer to the empirical statistics of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 20, and the Ljung-Box (1978) tests for autocorrelations of order 20 applied to standardized residuals in levels and squared standardized residuals respectively. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5%, and 1% levels respectively.

Table 4
Estimates of VARMA-GARCH(1,1) model with DCC structure for oil and stock sectors in Taiwan

Variables	Market Index		Basic Materials		Consumer goods		Consumer services		Financials		Industrials		Technology		Telecommunications	
	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock
Conditional mean equation																
Constant	0.0037**	0.0012	0.0039**	0.0029**	0.0033*	0.0015	0.0039**	0.0005	0.0035*	0.00003	0.0038**	0.0010	0.0038**	0.0018	0.0038**	0.0007
Conditional variance equation																
Constant	0.0001***	0.00003***	0.0002***	0.00001***	0.0001***	0.0004***	0.00005***	0.00006***	0.0001*	0.00003*	0.0001***	0.0001***	0.0001***	0.00008***	0.00004***	0.00001***
$(\varepsilon_{t-1}^{O})^2$	0.0830***	0.0161	0.0728***	0.0197**	0.0789***	0.0007	0.0109***	0.0326***	0.0786*	0.0123	0.0869***	0.0367*	0.0803***	0.0072	0.0575***	0.0273***
$(\varepsilon_{t-1}^{S})^2$	-0.0204	0.0936***	0.0316	0.0735***	−0.0017	0.0624***	0.0163**	0.0341***	-0.0086	0.0736***	−0.0288*	0.1037***	-0.0186	0.1376***	0.0734***	0.0026***
h_{t-1}^{O}	0.8578***	0.0082	0.8502***	0.0035	0.8605***	0.0116	0.6714***	−4.6191***	0.8665***	0.0295	0.8603***	0.0074	0.8506***	0.0126	0.7759***	−0.5212***
h_{t-1}^{S}	0.0356	0.8790***	0.0027	0.9184***	-0.0026	0.9174***	6.0224***	1.2486***	-0.0619	0.9021***	0.0148	0.8331***	0.0717**	0.8185***	2.1628***	1.1031***
Dynamic Conditional Correlation (DCC)																
θ_1	0.0188***		0.0196***		0.0187***		0.00003		0.0159***		0.0189***		0.0172***		0.0007***	
θ_2	0.9803***		0.9759***		0.9805***		0.9796***		0.9831***		0.9810***		0.9802***		0.0000	
Average DCC	0.1176		0.1491		0.0701		0.0588		0.0809		0.0791		0.1196		0.1339	
Diagnostic statistics																
Log L	2097.5		2055.4		1958.7		2016.4		1999.9		1977.1		1970.7		2299.9	
JB	138.4+++	24.87+++	145.1+++	183.1+++	148.8+++	57.74+++	45.63+++	80.33+++	145.3+++	30.01+++	120.7+++	63.74+++	133.0+++	9.897+++	30.76+++	252.0+++
ARCH(20)	0.6077	0.7939	0.6183	0.5416	0.6212	1.0454	0.6351	1.2730	0.6316	0.5923	0.6440	0.3776	0.5997	0.7240	0.8041	0.8474
Q(20)	12.981	20.453	13.546	20.584	13.104	11.464	12.152	15.577	13.155	12.898	13.068	21.950	12.977	26.577	11.532	26.005
$Q^2(20)$	12.784	17.428	12.987	11.446	12.971	21.649	12.177	21.164	13.122	12.859	13.552	8.454	12.677	14.928	16.498	17.579

Notes: Oil and stock are oil price returns, stock sector index returns respectively. *, **, and *** indicate significance at the 10%, 5% and 1% respectively. Model is estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. The Log L (Log Likelihood) criterion measures the relative goodness of fit of the estimated model. JB, ARCH(20), Q(20), and $Q^2(20)$ refer to the empirical statistics of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 20, and the Ljung-Box (1978) tests for autocorrelations of order 20 applied to standardized residuals in levels and squared standardized residuals respectively. +, ++, and +++ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5%, and 1% levels respectively.

These findings may result from that fact that China's oil consumption has quadrupled during the last three decades, and it has become the second largest oil consumer only after the US. At the same time, because the domestic oil production of China has slowed down since 1997, the increase in consumption is mainly satisfied by increases in import such that China turns from an oil export country into the world's second largest country of oil import and has become an oil pricing power in the world oil markets (see Li and Lin, 2011). One would expect fluctuations in oil markets would have a significant impact on China's stock market as a result, It is therefore surprising to find the evidence that China's stock market do not react to fluctuations in oil prices The possible reason is that given the elastic labour supply due to the large reserves of workforce of the Chinese economy, the oil price fluctuations harm China's export capacity less than that of its competitors and then ensures its ability of channelling the shocks originated from the world markets to its export destinations, which play an important role in decreasing China stock market volatility in the presence of oil shocks. Unambiguously, with its amount of oil consumption, higher dependence on imported oil supply and more market-oriented domestic oil pricing mechanism, the interactions between the world oil price and China's macro-economy and its stock market should have been more significant (Du et al., 2010), which indicates the necessity of government intervention regarding how to alleviate the impact of oil price fluctuations on equity markets.

In comparison with China, it is not surprisingly to observe that Hong Kong and Taiwan stock markets do not account for changes in the volatility of the world oil markets as Hong Kong and Taiwan imported only 2% and 4% worldwide oil trade volumes respectively. Hong Kong, on the other hand, is a service economy where the service sectors generated 92% of its GDP. It is short of China's ability to channel oil shocks to its export destinations, and its labour supply is inelastic due to the short reserves of workforces of the Hong Kong economy. Both factors may have contributed to the increase in Hong Kong stock market volatility with respect to increased fluctuations of oil prices. Finally, it is surprising to find that no volatility spillover effects from the world oil markets being transmitted to Taiwan stock market. A possible explanation is that Taiwan's export-oriented economy is not energy intensive, that is, oil is not a significant input in its production and, therefore, increases in oil price volatilities have little effect in its stock market volatility.

4.2 Volatility transmissions: the sector-level perspective

Basic materials. The results for oil and basic materials models in Greater China are similar in that there is evidence that past oil market shocks make a significant impact on the conditional volatility of Basic Materials stocks at least at the 10% level and that spillover effects in the opposite direction are statistically insignificant. An apparent difference observed among the three regions is the significant increase (decrease) in the volatility of the Hong Kong (China) Basic Materials sector with respect to changes in past oil volatility. A rationale may be that increased uncertainty in oil markets encourages the China Basic Materials sector to switch to the substitute coal sector, ameliorating its profitability and risk at the same time, which is obviously not the case of Hong Kong. As the relatively heavy use of oil in the Basic Materials sectors may be a key determinant of the oil effects (Arouri et al., 2011a), it is their own interest to increase their hedging activity in response to increased volatility of the oil markets.

Consumer Goods. The oil markets and the Consumer Goods sector in Hong Kong and Taiwan experience no significant direct cross-volatility effects. Their conditional volatility depends only on own past return innovations and own past volatility. The results for the China Consumer Goods sector are completely different as significant bilateral volatility transmission is observed. There are two possible reasons for these findings. First, the fact that the three subsectors (Automobiles & Parts, Food & Beverage, and Personal & Household Goods[15]) covered by the Consumer Goods sector are not export-oriented industries in China, which indicates that companies in these industries are not able to divert volatility transmission originated from the world oil markets to overseas, is the most likely explanation of the positive dependence of the China Consumer Goods sector to past volatility in the world oil markets in the long run. Moreover, companies operating in the Consumer Goods sector in Hong Kong and Taiwan may manage oil risk more efficiently than their counterparts in China, which plays an important role in reducing the sensitivity of this sector to oil shocks.

[15] This is due to the definition provided by DataStream.

Consumer Services. The oil markets and the Consumer Services sector in Greater China reveal the similar patterns as significant bilateral volatility spillover is observed. An apparent difference observed among the three regions is the significant increase (decrease) in the volatility of the Hong Kong (China and Taiwan) Consumer Services sector with respect to changes in past oil volatility. Among the three subsectors (Retail, Media, Travel & Leisure[16]) included in the Consumer Services sector, only Travel & Leisure subsector is a direct and heavy user of petroleum and related products. The negative values associated with volatility transmission in China and Taiwan suggest that these industries either have been benefiting from oil price fluctuations or successful at hedging or shifting the higher costs to the buyers of their products.

Financials. The results for the oil-financials model reveal only unilateral volatility spillover is observed. In fact, past oil shocks and volatility are found to drive down volatility in China Financials sector, whereas volatility in Hong Kong Financials sector is mainly driven up by past oil volatility, although it has somewhat similar exposure to unexpected oil shocks as China Financials sector. Surprisingly, there is no volatility reaction of Taiwan Financials sector with respect to past oil shocks or unexpected changes in past oil volatility. Although financial institutions are not directly involved with oil production or consumption, their association with oil occurs via their lending to and/or holdings of corporate bonds issued by firms with significant exposure to oil price fluctuations, their speculative positions in oil-related instruments, and portfolio readjustments that take place by market players in response to oil price movements (Elyasiani et al., 2011). The different spillover patterns may be explained by the degree of capital restriction and the financial sophistication among three regions. China has some of the most restrictive controls and uses them effectively to bias flows of cross border capital heavily, which has limited China's exposure to international capital markets. But Hong Kong allows capital to flow in and out of its financial markets without restrictions, except for the usual controls on money laundering and other criminal activity. The strict capital control in China may reduce its Financials sector's exposure to oil price fluctuations and the almost free-flow capital market in Hong Kong may play an important role in its positive reaction to oil price fluctuations. In addition, the fact that Taiwan capital market is not as mature and important as Hong Kong's is the most likely explanation of the disconnection between the world oil markets and Taiwan's Financials sector in terms of volatility transmission.

Industrials. The results for the oil-industrials model reveal a significant volatility transmission from the world oil markets to Industrials sectors in Greater China with respect to unexpected changes in oil returns and/or changes in past oil volatility. Only changes in the Taiwan Industrials sector returns and past volatility in China Industrials sectors, however, exert a significant impact on oil volatility at least at the 10% level. As a heavy user of petroleum and related products and the limited development of effective hedges against the impact of oil price fluctuations, it is not surprising to observe the volatility transmission effects for Industrials sectors in Greater China. Our results are the counterevidence of Malik and Ewing (2009), who note that the development of effective hedges against the effects of oil price changes is the most likely explanation of the insignificant volatility transmission from the world oil markets to the US Industrials sector.

Technology. For the oil-technology sector model, we essentially find bidirectional innovations and volatility transmission for China only, whereas the volatility cross effects run only from oil to Technology sector in Hong Kong and from Technology sector in Taiwan to oil. Increase in oil volatility may increase the speculations in Hong Kong technology companies, which make their stocks riskier.

Telecommunications. The oil-telecommunications sector models for Greater China show significant bilateral volatility spillover. Especially, the negative values associated with volatility transmission suggest that companies in this sector either have been benefiting from oil price fluctuations or successful at hedging or shifting the higher costs to the buyers of their products, which improves their stock performance and then makes their stocks safer.

In summary, the results from above various sectors imply interesting insights. China stock market, followed by the Hong Kong and Taiwan stock markets, has the closest link with the world oil markets in terms of volatility transmission at the sector stock levels. This is similar to the results

[16] This is due to the definition provided by DataStream.

at the country level of section 4.1. Moreover, the degree of volatility transmissions from oil market to sector stock markets varies from one sector to another, which is consistent to that of Arouri's et al. (2011a) with US and European experience. The variation may be dependent on industry-specific factors such as the degree of oil consumption, competition and concentration in the industry, and the effectiveness of hedging oil risk. This would have significant implication in portfolio diversification and hedging effectiveness, which will be further explored in Section 5.

4.3 Dynamic conditional correlations

The DCC estimates between pairs of sector stocks and corresponding Brent oil are also given in Table 2, 3 and 4. The significance of the DCC parameters, θ_1 and θ_2, in the Hong Kong and Taiwan stock markets indicates that the assumption of constant conditional correlation for all shocks to return is not supported empirically, which is also the case of China stock market as at least one DCC parameter is significant for five out of eight pairs of sector stocks and corresponding Brent oil. Furthermore, these estimated coefficients sum to a value which is less than one, indicating that the dynamic conditional correlations are mean-reverting.

The time-varying conditional correlations between the aggregate market indices and Brent oil market returns are given in Fig. 3.[17] It is clear that there is significant variation in the conditional correlations over time, especially in the returns of Brent and Hong Kong and Taiwan market indices returns. The dynamic conditional correlations can vary a lot from their average value emphasizing the need to compute dynamic conditional correlations. The period of the largest increases in conditional correlations was from July 2008 through December 2008. The conditional correlation reached its climax in September and October 2008, when Lehman Brothers' bankruptcy was announced. From November 2008 through August 2009, the conditional correlation decreased gradually, and stabilized thereafter. The dynamic conditional correlations between Brent oil and aggregate market index in China are all positive and have the lowest variation among three stock markets. The dynamic conditional correlations between Brent oil and aggregate market index in Hong Kong and Taiwan do alternate in sign and cover a relatively large range of value than China stock market. These periods of negative correlation provide an opportunity for effective portfolio diversification. Furthermore, the significant variation in the conditional correlations over time indicates that any inferences from the constant conditional correlation model would be misleading.

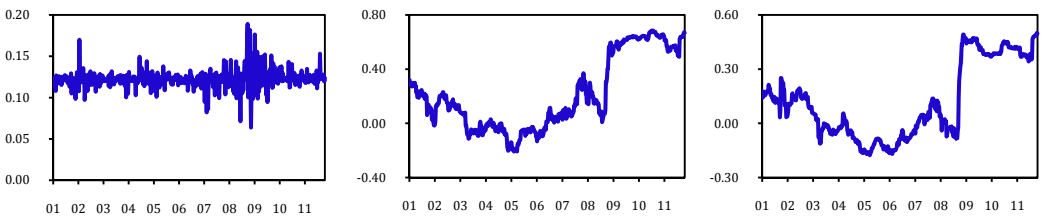

Fig.3 Time-varying conditional correlations computed from the VAR-GARCH model with DCC structure for pairs of market index and corresponding Brent oil in Greater China (from left to right: China, Hong Kong, Taiwan).

Diagnostic tests are presented in the lower part of Table 2, 3 and 4 for China, Hong Kong and Taiwan stock markets respectively. Tests on the standardized residuals and standardized residuals squared indicate that there are no significant signs of autocorrelation and ARCH effects at the 1% significance level. Moreover, by comparing the reported JB statistics shown in Table 1, we note that departure from normality are greatly reduced. Therefore, the VAR-GARCH model with DCC structure represents a parsimonious representation of the volatility process of oil and stock returns for Greater China.

5. Implications for optimal portfolio management

The additional source of uncertainty resulting from the strong connection between oil and stock markets in Greater China may present a new challenge, and the same time, a new opportunity to stock markets participants. Investors may need to re-evaluate their risk management strategies

[17] Due to space limitation, the DCCs of the oil-sectors stocks models in Greater China are not included in this paper and are available from the authors on request.

to deal with this additional source of risk. We apply our findings in Section 4 to two portfolio management strategies: optimal hedge ratio and optimal portfolio weight, which will be discussed in Section 5.1 and Section 5.2 respectively.

5.1 Optimal hedging ratio

Consider a long hedger investing in stock markets in Greater China who wishes to hedge its exposure to oil price movements. To minimize the underlying portfolio risk, the investor who has one local currency denominated stock index in Greater China should consider taking a short position of β_t^{SO} on the oil assets at time t, which is also called the Optimal Hedging ratio (OHR). Following Kroner and Sultan (1993), the OHR can be calculated as:

$$\beta_t^{SO} = \frac{h_t^{SO}}{h_t^{O}} \tag{9}$$

OHR is reported in Table 5 based on alternative MVGARCH models estimates. From the country level perspective, each MGARCH model provides an average OHR value of the Hong Kong market that is more than the China or Taiwan market, such that taking a long position in a Hong Kong stock portfolio requires more oil assets than shorting the same position in a China or Taiwan stock portfolio. For example, the VAR-GARCH model with DCC structure suggests that, in order to minimize risk for long hedgers, one HKD long in the Hong Kong market index is shorted by about 17.0 cents of oil futures, whereas only 9.3 cents and 9.8 cents of oil futures are needed for investors in the Taiwan and China stock markets respectively.

Table 5
Optimal hedging ratios for pairs of stock sectors and oil.

Portfolio	China			Hong Kong			Taiwan		
	BEKK	VAR-GARCH		BEKK	VAR-GARCH		BEKK	VAR-GARCH	
		CCC	DCC		CCC	DCC		CCC	DCC
Market Index/Oil	0.082	0.080	0.098	0.184	0.171	0.170	0.111	0.106	0.093
Basic Materials/Oil	0.149	0.128	0.162	0.250	0.222	0.233	0.126	0.127	0.120
Consumer Goods/Oil	0.030	0.001	0.018	0.131	0.126	0.100	0.099	0.101	0.064
Consumer Services/Oil	0.047	0.055	0.037	0.163	0.163	0.193	0.049	0.049	0.048
Financials/Oil	0.055	0.038	0.078	0.167	0.149	0.171	0.095	0.082	0.088
Industrials/Oil	0.065	-0.013	0.057	0.204	0.194	0.184	0.111	0.107	0.081
Technology/Oil	0.065	0.054	0.074	0.207	0.209	0.187	0.115	0.111	0.107
Telecommunications/Oil	0.092	0.114	0.094	0.148	0.138	0.121	0.066	0.057	0.068

Notes: This table reports average optimal hedging ratios of oil for an oil-stock portfolio using conditional variance and covariance obtained from alternative MGARCH models for each pair of oil/stock sectors: BEKK-GARCH(1,1), VAR-GARCH(1,1) with CCC structure, and VAR-GARCH(1,1) with DCC structure. For all models considered, the conditional mean equations contain a constant term. The oil asset is represented by the Brent crude oil of front month future contracts, whereas investment in stocks is represented by the DataStream Global Country Indices (China, Hong Kong and Taiwan) or each of seven stock sector indices in Greater China represented by the DataStream Global Sector Indices

By sectors, we see significant variation in the OHR's for the different sectors for the long hedgers investing in Greater China stock markets, ranging from the largest ratio, 23.3 cents, for the oil and Hong Kong Basic Materials sector to the lowest ratio, 1.8 cents, for the oil and China Consumer Goods sector in terms of the VAR-GARCH model with DCC structure estimates. Similarly as observed from the market level, Hong Kong stock market records the highest OHR value for each individual sector in comparison with its counterpart in the China and Taiwan stock markets. Furthermore, there are not particularly different across alternative models for each sector.

5.2 Optimal portfolio weight

In the portfolio diversification practice within the framework of the mean-variance optimization model (Markowitz, 1952), an efficient set of portfolios is created by maximizing the expected returns of the portfolio and minimizing its risk as measured by the standard deviation. According to Kroner and Ng (1998), the optimal portfolio weight of oil-stock holdings is given by:

$$w_t^{SO} = \frac{h_t^{S} - h_t^{SO}}{h_t^{O} - 2h_t^{SO} + h_t^{S}} \tag{10}$$

and

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

where h_t^O and h_t^S are the conditional variances of the oil market and the stock market (sector) respectively. h_t^{SO} is the conditional covariance between oil and stock returns at time t. w_t^{SO} *and* $(1 - w_t^{SO})$ are the optimal weight of the oil and stock holding respectively in a one-dollar oil-stock portfolio at time t. For example, for a one dollar portfolio, w^{SO} dollar is allocated to stock and $1 - w^{SO}$ dollar is allocated to oil assets.

The average values of realized optimal weights w_t^{SO} based on three MVGARCH models (BEKK, CCC, DCC) estimates are reported in Table 6. From the country level perspective, the average value of w_t^{SO} from the VAR-GARCH model with DCC structure is 0.369, 0.243, and 0.312 for stock markets in China, Hong Kong and Taiwan respectively. This suggests that the optimal holdings of stock in one RMB (HKD, TWD)[18] of oil-stock portfolio be 63.1% 75.7%, and 68.8% for stock markets in China, Hong Kong and Taiwan respectively. These optimal portfolio weights suggest that investors should have more stocks than crude oil in their portfolio in order to minimize risk without lowering expected returns. It also suggests that Hong Kong investors should hold the fewest oil assets, followed by Taiwan and China investors. This is not surprising, given that the average value of the DCC coefficient between oil and Hong Kong stock market is the highest. This finding also suggests that China investors have the lowest exposure to oil price movements as they can hold more oil assets, which corresponds to our previous analysis that China has the ability to divert the oil risks to its export destination. All the optimal weights results are confirmed by the estimates of the other two models (the VAR-GARCH with CCC structure and the BEKK), which gives very similar results.

Table 6
Optimal portfolio weights for pairs of stock sectors and oil.

Portfolio	China			Hong Kong			Taiwan		
	BEKK	VAR-GARCH		BEKK	VAR-GARCH		BEKK	VAR-GARCH	
		CCC	DCC		CCC	DCC		CCC	DCC
Market Index/Oil	0.362	0.371	0.369	0.245	0.242	0.243	0.317	0.318	0.312
Basic Materials/Oil	0.478	0.465	0.462	0.447	0.429	0.453	0.358	0.353	0.353
Consumer Goods/Oil	0.419	0.415	0.417	0.370	0.358	0.366	0.447	0.446	0.436
Consumer Services/Oil	0.426	0.432	0.436	0.308	0.339	0.297	0.410	0.401	0.398
Financials/Oil	0.419	0.426	0.432	0.262	0.251	0.269	0.404	0.410	0.414
Industrials/Oil	0.425	0.431	0.426	0.327	0.328	0.339	0.466	0.464	0.462
Technology/Oil	0.474	0.481	0.481	0.515	0.510	0.513	0.439	0.436	0.421
Telecommunications/Oil	0.603	0.598	0.603	0.431	0.392	0.415	0.173	0.150	0.172

Notes: This table reports average optimal weight of oil for an oil-stock portfolio using conditional variance and covariance obtained from alternative MGARCH models for each pair of oil/stock sectors: BEKK-GARCH(1,1), VAR-GARCH(1,1) with CCC structure, and VAR-GARCH(1,1) with DCC structure. For all models considered, the conditional mean equations contain a constant term. The oil asset is represented by the Brent crude oil of front month future contracts, whereas investment in stocks is represented by the DataStream Global Country Indices (China, Hong Kong and Taiwan) or each of seven stock sector indices in Greater China represented by the DataStream Global Sector Indices

Turning to the sectors perspective, which offers many detailed insights, it has been shown that the optimal weights for the oil asset in the hedged portfolios vary substantially across sectors and markets (China, Hong Kong and Taiwan), but they are not particularly different across alternative models. In terms of the VAR-GARCH models with DCC structure, the realized optimal weights w_t^{SO} varies from the lowest value of 0.417 recorded in the Consumer Goods sector to the highest value of 0.603 recorded in the Telecommunications sector for the China sector-based portfolios. This result indicates that for Consumer Goods sector the optimal allocation for oil in a one-RMB oil-stock portfolio should be 41.7 cents, with the remainder, 58.3 cents, invested in the Consumer Goods sector index. For Telecommunications, these optimal investments are 60.3 cents for oil and 39.7 cents for sector index. The VAR-GARCH models with DCC structure also reveal the realized optimal weights w_t^{SO} ranging from 0.269 (Financials) to 0.513 (Technology) for the Hong Kong

[18] RMB is the Renminbi, HKD is the Hong Kong dollar, and TWD is the New Taiwan dollar.

stock market, and from 0.172 (Telecommunications) to 0.462 (Industrials) for the Taiwan stock market. On the whole, our results suggest that, to minimize the risk without lowering expected returns, investors in Greater China should have more sector stocks than oil in their portfolio, except for the Hong Kong Technology sector and China Telecommunications sector, in which investors should hold more oil assets than sector indices in their optimal portfolios.

The information flow between stocks and oil price implies that the oil assets can be used as hedging instruments to diversify away the risk related to oil that influences stock portfolios. We follow Arouri's et al. (2011a) method to build two portfolios: an unhedged portfolio (stocks only) and a hedged portfolio (stocks and oil assets) with the optimal weights calculated above. According to Ku et al. (2007), the hedging performance of the portfolio diversification is evaluated in terms of the effects on the reduction of the variance of the investor's portfolio return. Thus, a hedging effective index (HE) is given as:

$$\mathrm{HE} = \left[\frac{\mathrm{var}_{unhedged} - \mathrm{var}_{hedged}}{\mathrm{var}_{unhedged}}\right] \tag{11}$$

where the variance of the hedged portfolios is obtained from the variance of the return on the oil-stock portfolios, and the variance of the unhedged portfolio is the variance of the return on the portfolio of stocks. A higher HE ratio indicates a higher hedging effectiveness and larger risk reduction, such that a hedging method with a higher HE implies that the underlying strategy can be regarded as a better hedging strategy.

Table 7
Comparison of hedging effectiveness (%) for designed portfolio in presence of the oil asset.

Portfolio	China			Hong Kong			Taiwan		
	BEKK	VAR-GARCH		BEKK	VAR-GARCH		BEKK	VAR-GARCH	
		CCC	DCC		CCC	DCC		CCC	DCC
Market Index/Oil	**30.561**	30.543	30.552	12.769	12.773	**12.774**	24.156	**24.157**	24.149
Basic Materials/Oil	**41.623**	41.502	41.470	35.227	34.861	**35.353**	**27.749**	27.487	27.486
Consumer Goods/Oil	41.400	41.387	**41.401**	29.981	29.954	**29.982**	38.227	38.231	**38.252**
Consumer Services/Oil	43.646	43.710	**43.752**	**20.629**	20.512	20.580	36.410	36.467	**36.475**
Financials/Oil	**36.427**	36.388	36.325	14.652	14.634	**14.653**	34.261	34.273	**34.275**
Industrials/Oil	40.094	**40.116**	40.097	21.385	21.389	**21.406**	39.805	39.808	**39.810**
Technology/Oil	**43.813**	43.807	43.806	39.515	39.514	**39.519**	**37.148**	37.131	37.008
Telecommunications/Oil	56.190	**56.192**	56.190	**33.936**	33.588	33.864	**12.983**	12.706	12.979

Notes: This table presents with comparison of hedging effectiveness ratios under three alternative MGARCH models. The Eq. (11) is conducted to calculate the percentage of risk reduction of hedged portfolios. Greater numerical values (Numbers in boldface) indicate the hedged portfolio with higher hedging effectiveness. The portfolio is a weighted oil-stock portfolio in which the weights are given by the optimal weights reported in Table 5.

A summary of hedging effectiveness documented in Table 7 shows that all numbers are positive, implying the superior performance of hedged portfolios (stock and oil asset) over unhedged portfolios (stock only). Consistent to the empirical results in Section 4, China's hedging effectiveness have similarities to that of Taiwan but not that of Hong Kong, reflecting the distinctive economic structure of individual regions. Furthermore, hedging performances varies substantially across sectors and markets (China, Hong Kong and Taiwan), but are not significantly different across different estimation models, which corresponds with Moosa's (2003) conclusions that the use of alternative models and method does not make any significant difference for hedging effectiveness. It also indicates that all three MGARCH models effectively reduce the variances of the portfolio, and perform better in the China stock market than the Hong Kong and Taiwan stock markets. Of the MGARCH models, the optimal model is the VAR-GARCH model with DCC structure leading to the highest hedging effectiveness in twelve out of twenty-four pairs of oil-stock markets (sectors), followed by the BEKK-GARCH and VAR-GARCH model with CCC structure prevailing in nine and three out of twenty-four cases respectively, which indicates the superior diversification benefits in terms of risk reduction provided by the VAR-GARCH model with DCC structure compared to the VAR-GARCH approach with CCC structure or the BEKK-GARCH model.

6. Conclusion

This paper investigates the extent of information flow between oil markets and stock markets and its seven sub sectors in China, Hong Kong and Taiwan with three MGARCH models (DCC, CCC and BEKK). We find strong evidence in support of the view that oil price fluctuations constitute a systematic asset price risk at the sector level, as nineteen of the twenty-four sectors (markets) analyzed show statistically significant volatility spillovers originated from either past oil shocks or past volatility of oil. We also find that the effects of volatility transmission in pairs of oil and stock markets (sectors) are dissimilar across markets (sectors) in the sense that the oil price fluctuaitons exert more influence on the stock market (sectors) in China than in Hong Kong and Taiwan. It appears that the equity market is able to discriminate the effects of oil price movements based on the characteristic of the underlying economy system in terms of different economic structure, energy intensity, energy mix and dependence on the international energy market. Furthermore, we find that the correlations between oil and stock markets (sectors) are time-varying and must be modelled as such. We further apply our findings to calculate optimal oil-stock portfolio weights, hedging ratios and improve optimal portfolio designs. Our results show that information content embedded in oil market volatility is an effective and valuable variable for constructing an optimal oil-stock holding, as indicated by the superior hedging effectiveness of the hedged oil-stock portfolios than traditional portfolios of stocks. It would have significant implications to investors, fund managers, risk manager and other stock and oil market participants operating in Greater China area.

Future research may focus on simulation and analysis of government intervention regarding how to alleviate the impact of oil price fluctuations on equity markets. Additional insight may also be gained by exploring regime changes in the role of oil price fluctuations in explaining the equity market behaviour.

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