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Dynamic Correlations and Volatility Spillovers between Crude Oil and Stock Index Returns: The Implications for Optimal Portfolio Construction

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ABSTRACT: This paper researches the portfolio construction between stock price of group of seven (G7) and West Texas Intermediate crude oil from January 2, 1998 to March 1, 2012. We investigate the volatility spillover between stock price and oil price with the dynamic conditional correlation (DCC), constant conditional correlation (CCC) and BEKK models, and also analyze their optimal hedge ratio and portfolio weights. The empirical result is that the hedge effectiveness of DCC model is better than the CCC model and BEKK models. The hedge effectiveness (HE) in Canada is the highest but Japan is the lowest. Moreover, the results show that Japan has the biggest optimal portfolio weight and the lowest hedge ratio. We do this research with expectation of providing investors information to increase the basis of investing.

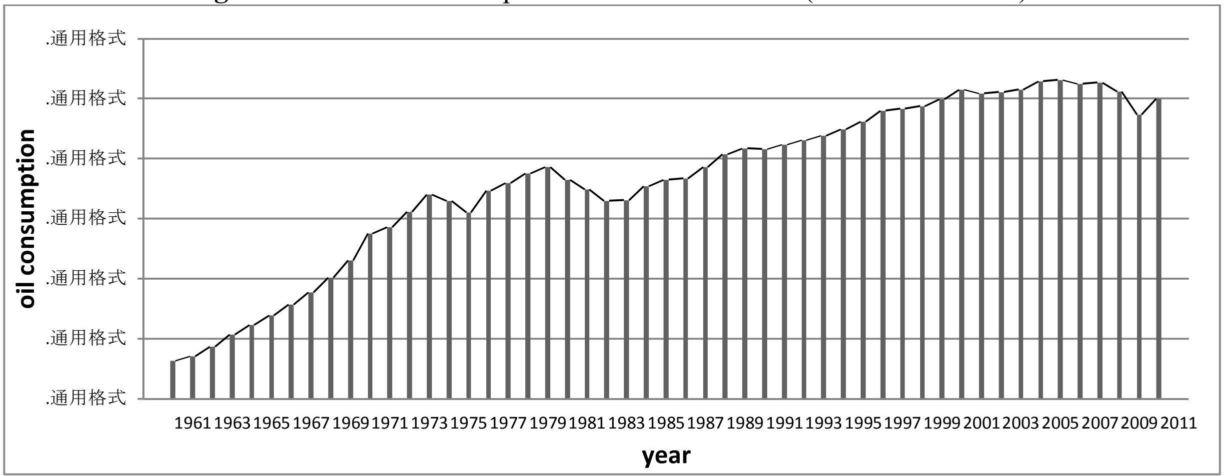
Keywords: Crude oil; DCC model; Hedge effectiveness; Optimal portfolio
JEL Classifications: C22; G1; N7

1. Introduction

The G7 is one of the most influential institutions for international policy coordination and global economic governance.[1] The member countries attend a summit every year and discuss global issues such as macroeconomic management, international trade and relations with developing countries. In recent years, they have also focused on energy. With the economic growth, the demand for crude oil of industrial countries is increasing gradually. Besides, the volatility in oil prices affects economic growth. The reason for choosing the G7 countries as the main objects is that they have an economic influence. In addition, many researchers use the G7 as their study object, and the range of study topics is wide, including such subjects as the business cycle of G7 countries (Narayan and Popp, 2009) and the long memory in the G7 stock market (Bilel and Nadhem, 2009). However, relatively few papers examine the impact of changes in real oil prices on the real stock returns of G7 countries and find crucial implications for the linkage between oil and stock markets (Lee et al., 2012; Lee and Zeng, 2011). Moreover, Figure 1 shows that oil consumption from 1960 to 2011 increased and indicates that oil still plays an important role in economic development and is sure to influence the stock price.[2] Accordingly, we think that the results of this study will provide investors with a great deal of information to apply.

[1] The G7 (Canada, United Kingdom, France, Germany, Italy, Japan and America) was created in 1975.
[2] http://data.worldbank.org/topic/energy-and-mining

Figure 1. Total oil consumption of the G7 countries (ten thousand tons)



Since the nineteenth century, oil has come to replace coal as the key to economic growth. In recent years, the demand for crude oil has risen constantly; even if crude oil is used more efficiently, the storage of crude oil has declined, resulting in price increases and causing the economy to become unstable. The oil price has a high correlation with the energy price and chemical raw materials price. Therefore, oil price rises will dramatically increase the cost of production and cause inflation. Then, investors' disposable income will decrease, generating an adverse impact on the economic growth. Conversely, a stable price and economic growth will stimulate a boom. Consequently, a change in the oil price has a whole and active effect on the change in the price of goods. It is apparent that research on the financial market; energy-related industries and macro economy always uses crude oil as the object. An increase in the oil price has a negative impact on almost all countries and industries except for mining, oil-related and gas-related industries (Cong et al, 2008; Nandha and Faff, 2008; Park and Ratti, 2008). In addition, an increase in the oil prices leads to a higher probability of a bear market emerging (Chen, 2010). Most of these papers investigate the constant correlation between oil price and stock price (Chang et al., 2013). However, the hypothesis of constant correlation is not tenable in reality. These reasons mean that the dynamic correlations between oil prices and stock prices cannot be ignored. Therefore, the DCC model, which has the time-varying correlation coefficient, is applied in this study and then the results are compared with the CCC model and the BEKK model. In addition, volatility spillover is important for realizing the information flow and risk transfer between markets. A volatility spillover occurs when changes in volatility in one market produce a lagged impact on volatility in other markets. Lin and Tamvakis (2001) and Milunovich and Thorp (2006) suggested that volatility spillover appears widely in energy markets and financial markets, respectively. Consequently, it is valuable to measure the volatility spillover for investment portfolios and risk management. Therefore, this study uses three multivariate GARCH models including the volatility spillover.

Today, the rising price of crude oil is increasing the cost of almost all industries and decreasing the profit, causing the stock price of the industries to fall. Therefore, investors are changing their thoughts about risk management. Many hedging strategies are emerging. How to choose hedging commodities and how to construct optimal portfolio weights have become very important questions to investors. It has becomes a trend to construct a hedging portfolio by using crude oil. In addition, the volatility spillover relationships between two markets are crucial for constructing hedge ratios and optimal portfolios (Arouri et al., 2012; Chang et al., 2010). Although Chang et al. (2011) used four multivariate GARCH models and found the dynamic conditional correlations between Brent forward returns and FTSE100 are high; they didn't apply the result to estimate the hedge ratios. Consequently, this study uses three multivariate GARCH models to analyze the portfolio between G7 stock price indexes and oil prices.[3] Then, we also explore the hedge effectiveness, the optimal hedge ratio and the

[3] First, the CCC model, proposed by Bollerslev (1990), assumes that the conditional correlation is constant. Nevertheless, this hypothesis conflicts with reality in that the correlation coefficient between the financial assets is not constant. Engle and Kroner (1995) introduced the BEKK model, which solves the problem that the

optimal portfolio weights.

After some model tests and exploring the hedge effectiveness, optimal hedge ratio and optimal portfolio weights, we show the weighting, beta and correlation tendencies with some major financial or international events marked in the figure. The weighting tendency represents how much weight is invested in oil. The beta indicates how much a one-dollar long position in the stock price index can be hedged with a short position in the oil market. Finally, correlation tendency shows that the connections between the oil market and the stock price indices of these countries should not be ignored. We combine these figures for ease of comparison.

We hope that our empirical study can contribute to this field of research by using three GARCH models (BEKK, CCC and DCC) to compare the hedge effectiveness and estimate the optimal hedge ratio and portfolio weights between the oil price and the stock price of G7 countries. As many researchers have pointed out, it is important to estimate optimal hedge ratio and portfolio weights so that investors can have more information at their disposal when carrying out a hedge strategy (Huisman et al., 2009; Yao and Wu, 2012). Although innumerable empirical studies of hedging have been presented, most of them concern countries in the same area (Arouri et al., 2012; Lai and Tseng, 2010). Therefore, the present study fills a gap in the literature by researching an age-old international organization.

The present empirical study is organized in several sections. Section 2 presents the data and empirical model that we use in the study. Section 3 shows our empirical results, and Section 4 concludes the paper.

2. Data and Empirical Model

2.1 Data

The data for this study includes the stock price indexes of the G7 (Canada, England, France, Germany, Italy, Japan and America)[4] and the West Texas Intermediate crude oil price. We use the data to analyse the hedge effectiveness, optimal hedge ratio and portfolio weights. The sample period for the data set extends from 2 January 1998 to 1 March 2012. All these data are available from Datastream. The formula for the return is $R_t = \ln(\frac{p_t}{p_{t-1}})$. p_t is the daily closing price.

2.2 Empirical model

In this study, three GARCH models (BEKK, CCC and DCC) are used. BEKK model is given by:

$$R_t = \mu + \sum_{i=1}^{n} R_{t-i} + \varepsilon_t \quad (1)$$

with the setting $\varepsilon_t \mid \Phi_{t-1} \sim N(0, H_t)$, and

$$H_t = C_0' C_0 + \sum_{k=1}^{K} C_{1k}' x_t x_t' C_{1k} + \sum_{k=1}^{K} \sum_{i=1}^{q} \Gamma_{ik}' \varepsilon_{t-i} \varepsilon_{t-i}' \Gamma_{ik} + \sum_{k=1}^{K} \sum_{i=1}^{p} B_{ik}' H_{t-i} B_{ik} \quad (2)$$

Equation (1) represents the conditional mean. R_t, μ and ε_t are the return vector, the vector of the constant, and the residual vector, respectively. Equation (2) is the conditional variance–covariance matrix. C_0 、C_1 、Γ_{ik} and B_{ik} are n*n parameter matrices with a lower triangular. Γ_{ik}, i=1,…,q, k=1,…,K, and B_{ik}, i=1,…,p, k=1,…,K. x_t is a J*1 vector of exogenous variables. Moreover, the covariance matrices in the BEKK model are assumed to be positive definite. The conditional variance of the CCC model is defined as:

$$\mathrm{var}(\varepsilon_t \mid \Phi_{t-1}) = D_t \Gamma D_t \quad (3)$$

$D_t = \mathrm{diag}(h_1^{1/2}, \ldots, h_m^{1/2})$ and m is the number of variables. $\Gamma = E(\eta_t \eta_t' \mid \Phi_{t-1}) = E(\eta_t \eta_t')$, where $\Gamma = \{\rho_{ij}\}$ for i,j=1,2,…,m. $D_t \Gamma D_t$ is the conditional covariance matrix. The conditional variance is positive definite if and only if all the conditional variances are positive and the correlation matrix $\Gamma = \{\rho_{ij}\}$ is positive definite.

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conditional variance in each model is hard to be positive definite. However, the BEKK model is not always positive definite and the parameters of this model are too numerous. Thus, Engle (2002) revised the defects of the CCC model to develop the DCC model. The defects were conducted by changing the correlation coefficient and decreasing the matrix estimated parameters. The DCC model has the time-varying correlation coefficient and retains the simple estimated formula of the CCC model.

[4] S&P/TSX composite index, FTSE 100, France CAC 40, DAX 30 performance, FTSE MIB index, Nikkei 225 stock average and S&P 500 composite are used for Canada, England, France, Germany, Italy, Japan and America.

To make the conditional correlation matrix change with time, the DCC model is amended from the CCC model. The conditional correlation matrix of the DCC model is:

$$Q_t = \bar{\rho}(1 - \lambda_1 - \lambda_2) + \lambda_1(\varepsilon_{t-1}\varepsilon'_{t-1}) + \lambda_2 Q_{t-1} \quad (4)$$

$\bar{\rho}$ is the unconditional correlation matrix. λ_1 and λ_2 are two non-negative scalar parameters and $\lambda_1 + \lambda_2 < 1$. When $\lambda_1 = \lambda_2 = 0$, the DCC model is equal to the CCC model.

This study uses these three models to analyze the hedge effectiveness, optimal hedge ratio and portfolio weights. Besides, hedge effectiveness (HE) is:

$$HE = \frac{\sigma_u^2 - \sigma_h^2}{\sigma_u^2} \quad (5)$$

σ_u^2 is the variance of the rate of return of the spot before hedging. σ_h^2 is the variance of the rate of return of the spot after hedging. The difference between σ_u^2 and σ_h^2 divided by σ_u^2 represents hedge effectiveness. It represents hedge effectiveness of each country by hedging with oil. This paper shows the result of three models and makes comparison. The value is the higher the better.

The model for the optimal portfolio weights is:

$$w_{so,t} = \frac{h_{s,t} - h_{so,t}}{h_{o,t} - 2h_{so,t} + h_{s,t}} \quad (6)$$

$$w_{so,t} = \begin{cases} 0, \text{if } w_{so,t} < 0 \\ w_{so,t}, \text{if } 0 \leqq w_{so,t} \leqq 1 \\ 1, \text{if } w_{so,t} > 1 \end{cases} \quad (7)$$

$w_{so,t}$ is the optimal holding weight of oil in a one-dollar portfolio at time t. $h_{so,t}$ is the conditional covariance between the stock price index and the oil price, $h_{s,t}$ is the conditional variance of the stock price index and $h_{o,t}$ is the conditional variance of the oil price at time t. By design, the weight of the stock price index in the oil-stock portfolio is equal to (1-$w_{so,t}$). The optimal hedge ratio is:

$$\beta_{so,t} = h_{so,t}/h_{o,t} \quad (8)$$

The hedge ratio means that a long position of one-dollar on the stock price index must be hedged by a short position of $\beta_{so,t}$ dollars on the oil asset. $h_{so,t}$ is the conditional covariance between the stock price index and the oil price at time t and $h_{o,t}$ is the conditional variance of the oil price at time t.

3. Empirical Results

The basic statistics for the daily return of the G7 stock price indexes and oil price are shown in Table1, and the mean values are close to zero. For each series, the standard deviation is larger than the mean value. The mean values of Italy and Japan are negative while the rest are positive; the mean values of Japan are the lowest. In addition, the standard deviation of oil is the highest while that of Canada is the lowest. For each series, the skewness is smaller than zero. This indicates that the distribution trends left. The kurtosis values are greater than three. The Jarque-Bera test shows that the G7 and the oil price have a 1% significance level, that is, they do not follow normal distribution. Finally, there is a strong ARCH effect. The ARCH[5] test shows that all the series are at the 1% significance level.

Figure 2 shows a price chart of G7 stock price indexes and oil. The G7 stock price indexes (oil) correspond to the left axis (right axis) value. There are positive correlations between the G7 stock price indexes and the oil price. The stock price indexes of Canada, England and America have high correlations with the oil price. However, the stock price indexes of France, Germany, Italy and Japan have relatively low correlations with the oil price.

This study uses ADF and PP unit root tests to test whether the G7 stock price indexes and oil price are in a stationary state. The results of the unit root test of the original data and after the first difference data are shown in Table 2. C, C&T and Non represent intercept, intercept and trend and neither of the two, respectively. The results show that the original data of the G7 stock price indexes and oil price are not significant at 1%, that is they are not in a stationary state. After the first difference of all the data, the results show that they are significant at 1% and in a stationary state in the ADF test and PP test.

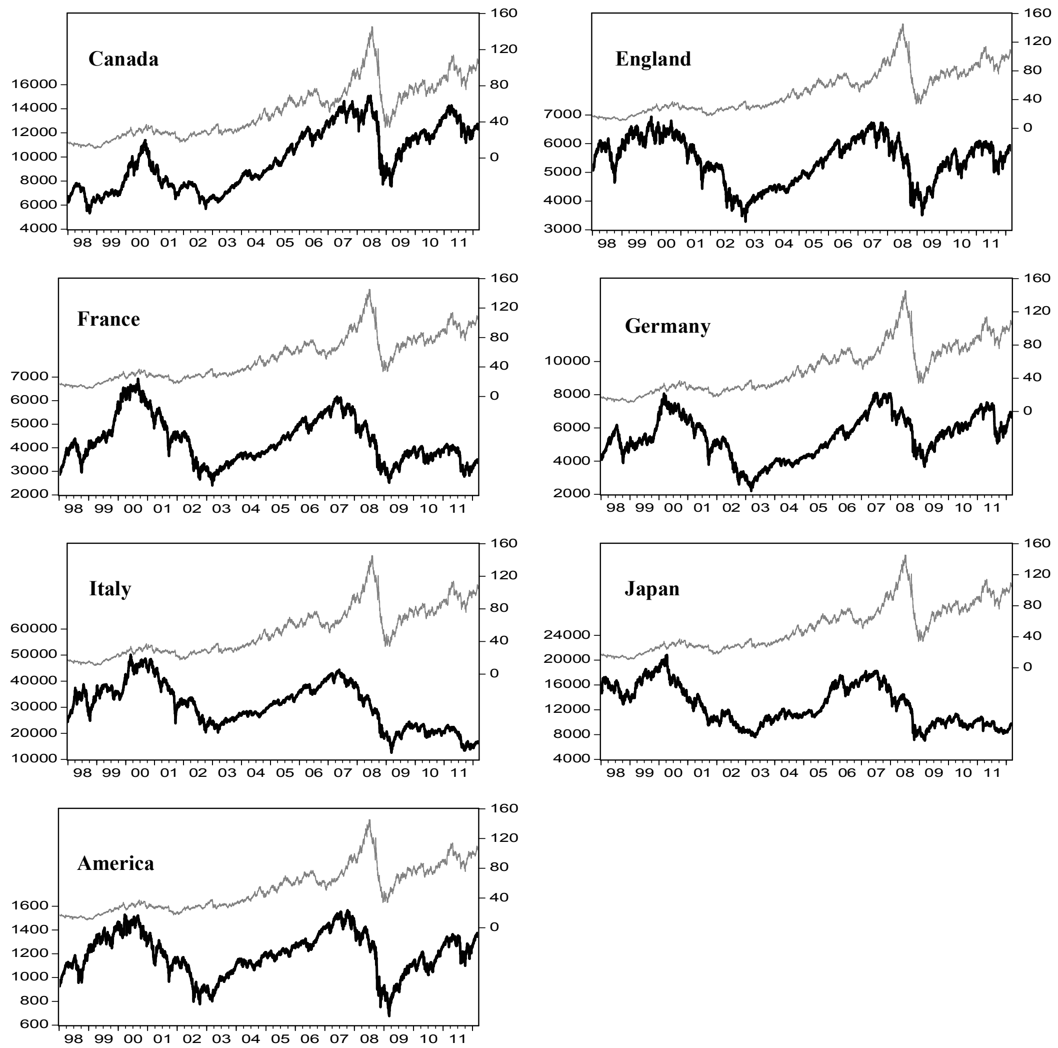
[5] Assuming the residuals of function is $e_t = v_t\sigma_t^2$ and $\sigma_t^2 = \omega + \alpha_1\sigma_{t-1}^2 + \alpha_2\sigma_{t-2}^2 + \cdots + \alpha_n\sigma_{t-n}^2 + \eta_t$. The hypothesis of ARCH model is H_0: $\sigma_t^2 = \omega$, representing $\alpha_1 = \alpha_2 = \cdots = \alpha_n = 0$.

Table 1. Basic statistics for daily return

	Mean	Std. dev.	Skewness	Kurtosis	Jarque-Bera	ARCH test
Oil	0.049	2.490	-0.136	7.247	2791.179***	67.0372***
Canada	0.017	1.211	-0.643	11.159	10513.740***	145.7017***
England	0.003	1.288	-0.132	8.357	4433.166***	200.8207***
France	0.003	1.548	-0.003	7.480	3093.604***	136.0094***
Germany	0.012	1.623	-0.052	6.863	2301.927***	139.6446***
Italy	-0.011	1.554	-0.090	7.559	3208.443***	141.8002***
Japan	-0.013	1.536	-0.333	9.583	6747.145***	302.3583***
America	0.009	1.332	-0.183	10.174	7952.843***	184.8854***

Note: *** Significant at 1%.

Figure 2. Price chart of G7 stock price indexes and oil.



(The G7 stock price indexes (oil) correspond to the left axis (right axis) value.)

Table 2. ADF unit root test

Sample	Level			1st		
	C	C&T	Non	C	C&T	Non
Oil	-1.078	-2.986	0.382	-46.061***	-46.058***	-46.045***
Canada	-1.539	-2.268	0.373	-61.381***	-61.373***	-61.379***
England	-2.121	-2.120	-0.150	-39.709***	-39.704***	-39.714***
France	-2.040	-2.358	-0.352	-38.328***	-38.345***	-38.333***
Germany	-1.929	-2.007	0.024	-60.498***	-60.490***	-60.503***
Italy	-1.174	-2.369	-0.608	-61.703***	-61.724***	-61.710***
Japan	-1.711	-1.988	-0.907	-62.135***	-62.127***	-62.140***
America	-2.430	-2.430	0.090	-65.540***	-65.532***	-65.546***
PP unit root test						
Oil	-0.988	-2.870	0.479	-63.121***	-63.116***	-63.108***
Canada	-1.457	-2.136	0.449	-61.519***	-61.511***	-61.513***
England	-2.195	-2.201	-0.128	-62.737***	-62.728***	-62.746***
France	-1.845	-2.186	-0.294	-62.430***	-62.458***	-62.439***
Germany	-1.874	-1.950	0.056	-60.534***	-60.525***	-60.538***
Italy	-1.160	-2.353	-0.605	-61.704***	-61.727***	-61.710***
Japan	-1.606	-1.875	-0.912	-62.265***	-62.256***	-62.267***
America	-0.988	-2.870	0.479	-63.121***	-63.116***	-63.108***

Notes: 1.*** Significant at 1%.
2. C, C&T and Non represent intercept, intercept and trend and neither of two, respectively.

Moreover, we conduct a test between the DCC model and the CCC model by using the Lagrange multiplier (LM) test, which only requires an estimation of the restrictions of the CCC model to complete the computation conveniently. The result is shown in Table 3. The result ranges from 15.268(Japan) to 95.687(Canada). All of the results reject the null hypothesis and are significant at 1%. That means that the DCC model is better than the CCC model for this research to estimate the hedge effectiveness, optimal portfolio weights and optimal hedge ratio.

Table 3. Model test

Country	Canada	England	France	Germany	Italy	Japan	America
F-value	95.687***	62.672***	53.255***	38.096***	50.277***	15.268***	35.186***

Note: *** Significant at 1%.

The hedge effectiveness, optimal portfolio weights and optimal hedge ratio of the DCC, CCC and BEKK models are shown in Table 4.[6] Panel A shows the value of the hedge effectiveness and optimal hedge ratio for each country. Panel A indicates that the value of hedge effectiveness of the DCC model ranges from 1.795 to 11.881, the result of the CCC model ranges from 1.247 to 9.050 and the result of the BEKK model lies between 1.673 and 10.202. Moreover, for each country, the hedge

[6]To ensure the accuracy of the model, we use the Ljung-Box Q to test residual autocorrelation. The result shows that they are all significant at 5%, except one of the items for Italy in the BEKK model. This means that there is no serial correlation at 5%. There is serial correlation in the BEKK model while there is no serial correlation in the DCC model and CCC model. Therefore, it is better to use the DCC model and the CCC model than the BEKK model to construct the optimal portfolio weights and the optimal hedge ratio.

effectiveness of the DCC model is higher than that of the CCC model and the BEKK model. The highest hedge effectiveness is in Canada, while the lowest is in Japan. It represents that Canada has the highest effectiveness in using oil to hedge risk among the G7 countries and Japan has the lowest. The hedge ratio of Canada is \$0.117, indicating that for a \$1 long position in Canada stock price index can be hedged for \$0.117 with a short position in the oil market. However, the hedge ratio of Japan is \$0.051. It means that when investing in Canada needs using more funds to hedge risk but Japan needs the least.

Table 4. Hedge effectiveness (%), hedge ratio and optimal portfolio weights

Panel A: Hedge effectiveness and hedge ratio						
Country	DCC	Hedge ratio	CCC	Hedge ratio	BEKK	Hedge ratio
Canada	11.881	0.117	9.050	0.118	10.202	0.120
England	11.004	0.090	5.192	0.082	9.967	0.086
France	9.406	0.106	4.246	0.090	8.977	0.097
Germany	7.480	0.090	2.464	0.077	7.085	0.082
Italy	10.134	0.105	4.428	0.076	8.082	0.095
Japan	1.795	0.051	1.247	0.045	1.673	0.049
America	8.305	0.073	3.497	0.056	7.444	0.068

Panel B: Optimal portfolio weights, EW and weighted									
Country	Weights	EW	OW	Weights	EW	OW	Weights	EW	OW
Canada	0.103	2.322	1.357	0.106	2.322	1.384	0.098	2.322	1.373
England	0.154	2.289	1.425	0.164	2.289	1.454	0.155	2.289	1.430
France	0.235	2.496	1.854	0.236	2.496	1.871	0.233	2.496	1.855
Germany	0.253	2.505	1.888	0.257	2.505	1.912	0.250	2.505	1.894
Italy	0.235	2.497	1.888	0.234	2.497	1.905	0.235	2.497	1.884
Japan	0.256	2.322	1.768	0.259	2.322	1.769	0.260	2.322	1.763
America	0.169	2.262	1.494	0.178	2.262	1.518	0.170	2.262	1.500

Notes: 1.Values in bold represent the biggest hedge effectiveness in the country.
2. EW and OW mean equal weighted variance and optimal weighted variance, respectively.
3. *** Significant at 1%.

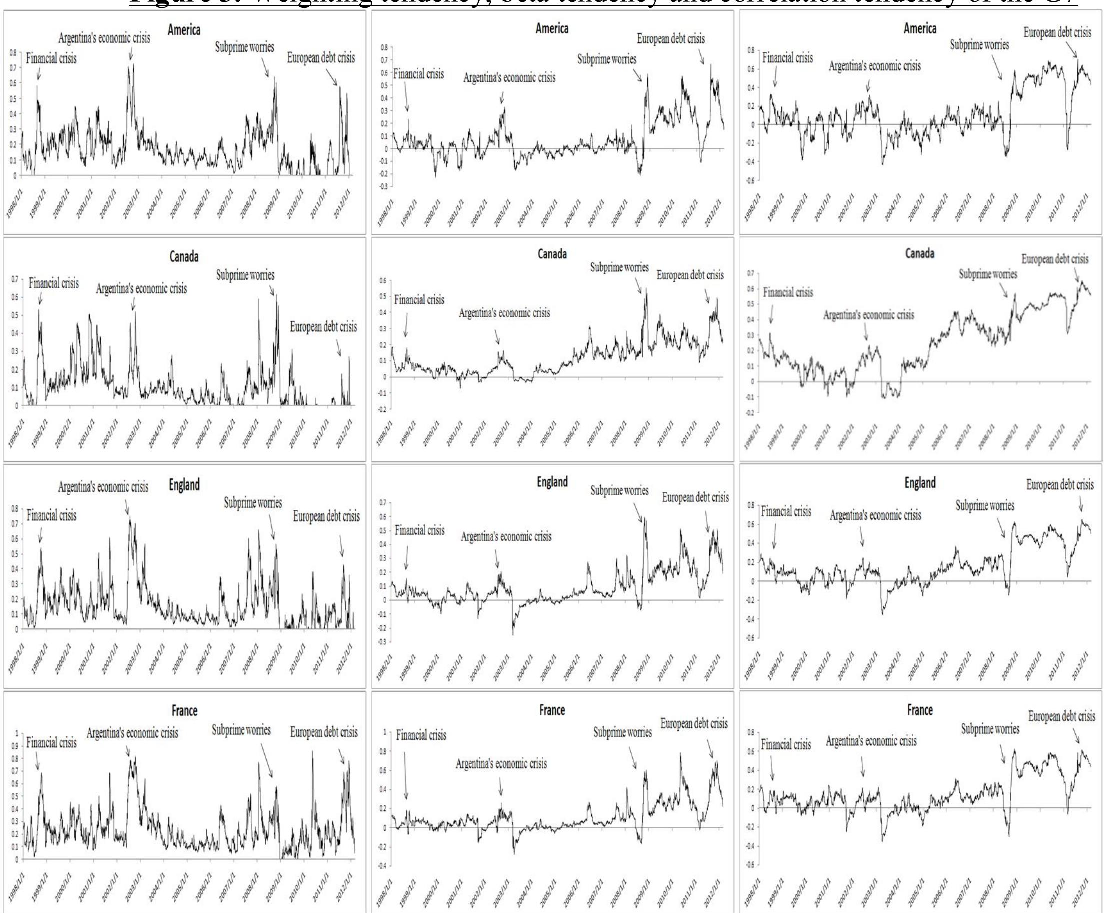
Panel B shows the optimal portfolio average weights, EW and weighted variance for each country. Taking Canada in the DCC model as an example, the average weight is 0.103, indicating that for a \$1 portfolio, \$0.897 should be invested in the Canada stock price index and \$0.103 invested in oil. The optimal portfolio weights of France, Germany, Italy and Japan are higher than those of the rest of the countries (Canada, England and America). Japan has the highest portfolio weight and the lowest hedge ratio while Canada has the lowest portfolio weight and the highest hedge ratio. In addition, the value of EW is bigger than that of OW for each series. This indicates that the portfolio following the optimally weighted method is better than the one following the equally weighted method. Germany has the biggest value of EW in the three models, while America has the smallest value. Besides, Germany has the biggest optimally weighted value while Canada has the smallest. Moreover, the range of the difference between EW and weighted of the DCC model is from 23.854 to 41.548, in the CCC model it is from 23.667 to 40.410 and in the BEKK model it is from 24.069 to 40.881.The biggest difference in the three models is in Canada. The smallest difference for the DCC model and the BEKK model is in Japan, while that for the CCC model is in Germany.

This study showed the weighting tendency, beta tendency and correlation tendency of the G7 as shown in Figure 3. The weighting tendency represents how much weight has been invested in oil in the last fourteen years in the G7 countries. Some obvious increasing tendencies are shown in the graph. When major international or financial events happen, investors may put more of their fund in oil than in the stock market, and this causes the weighting tendency to rise. In the beta tendency, the subprime worries and European debt crisis are more apparent than the financial crisis and Argentina's economic crisis. This shows that the impact of the subprime worries and European debt crisis on investors may have been greater than the impact of the other events. Therefore, they hedged the risk with more money. Ultimately, we can find that the correlation tendency for these countries rose from 1998 to 2012, demonstrating that the degree of correlation between stock price indices and oil prices became increasingly strong, as well as reminding investors not to neglect the importance of oil. Although the correlation tendency of Japan does not increase as much as that of the others, it is stable and still increased when major financial or international events occurred.

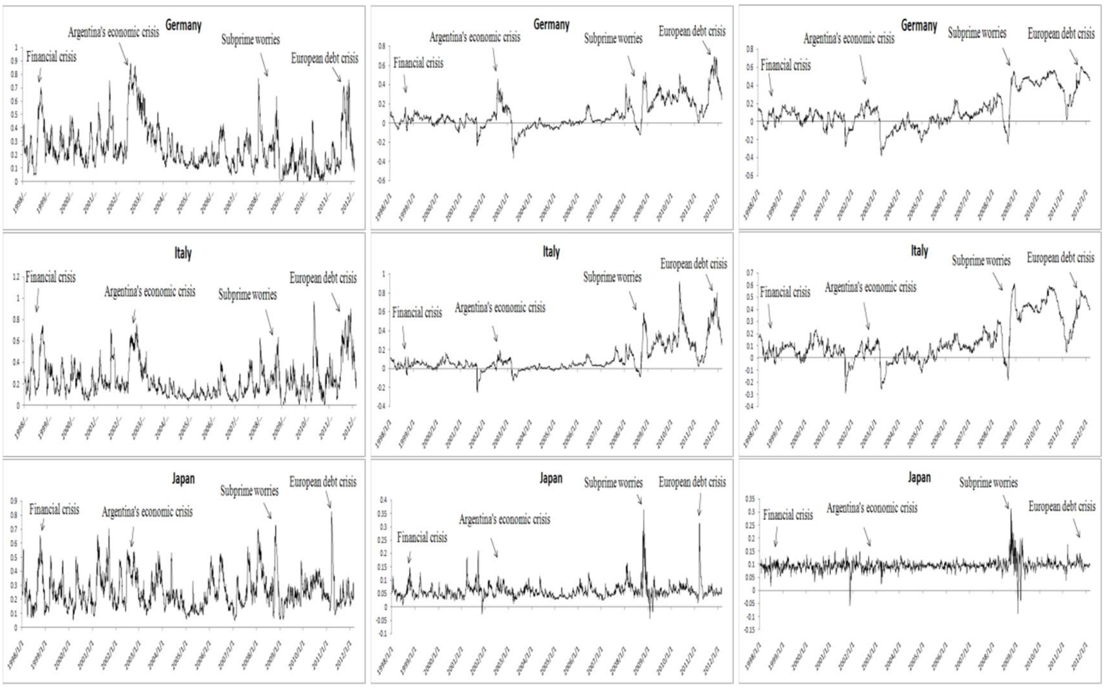
We present some major international or financial events, including

1. The Russian financial crisis (ruble crisis) took place on 17 August 1998. It made the Russian Government devalue the ruble and default on its debt.
2. The Argentinian economic crisis began in 1999 with a decrease in the real GDP.[7]
3. The subprime worries, from the middle of 2007 to the end of 2008, were caused by a rise in subprime mortgage delinquencies, foreclosures and a decline in securities backed by said mortgages.
4. The European debt crisis began at the end of 2009. It was caused by the fears of a sovereign debt crisis formed within the investors. The fears sprang from the rising private and government debt levels around the world and the downgrading of government debt in some European states.

Figure 3. Weighting tendency, beta tendency and correlation tendency of the G7



[7] Three serious crises explain why it happened. First, the Argentinian peso was bound to the US dollar in the early 1990s. Next, the Argentinian President borrowed large amounts of money. Finally, the debt increased because of the great shrinkage of the tax revenue.



(Weighting) (Beta) (Correlation)

4. Conclusion

In this study, multivariate GARCH models are used to analyse and compare portfolios regarding the stock price indexes of Canada, England, France, Germany, Italy, Japan and America and the oil price. The sample period for the data set covers 2 January 1998 to 1 March 2012. The empirical models include the CCC model, BEKK model and DCC model. Then, we further explore the optimal hedge ratio and the optimal portfolio weights.

The empirical results show that the DCC model is preferred to the CCC model and the BEKK model. Canada has the highest hedge effectiveness, while Japan has the lowest. Moreover, the optimal portfolio weights and hedge ratio are estimated by the three models. The results show that the optimal portfolio weights of France, Germany, Italy and Japan are higher than those of Canada, England and America. Because of the low correlation between the stock price index of Japan and the oil price, the optimal portfolio weight (hedge ratio) of Japan is higher (lower) than that of the other countries. Conversely, because of the high correlation between stock price index of Canada and the oil price, the optimal portfolio weight (hedge ratio) of Canada is lower (higher) than that of the other countries. In addition, the portfolio following the optimally weighted method is better than the one following the equally weighted method. Germany (Canada) has the biggest (smallest) optimally weighted value. Therefore, if investing in countries with a low hedge ratio, like Japan, America, Germany and England, we suggest that investors can construct a hedging strategy by the oil price. Finally, the weighting tendency, beta tendency and correlation tendency figures show that when major financial or international events occur, investors prefer to put their money in the oil market.

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