Dynamic correlation among East Asian stock markets and time-varying interdependence between East Asian stock markets and the prices of oil and gold

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Dynamic correlation among East Asian stock markets and time-varying interdependence between East Asian stock markets and the prices of oil and gold.

(東アジア株市場の相関関係、株市場と原油、ゴールド価格の依存関係について)

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Contents

Introduction

In our paper we employ various time series analysis including DCC-GARCH, DECO-GARCH, wavelet coherence analysis and copula functions to investigate the relationship between East Asian stock markets and between East Asian stock markets and the prices of crude oil and gold.

In Chapter 1 we investigate financial markets contagion between United States and eight East Asian emerging markets. We employed two types of models, the DCC-MGARCH and DECO-MGARCH models to examine the conditional correlations and equicorrelation among the emerging East Asian stock markets (Hong Kong, Thailand, Malaysia, Singapore, Indonesia, Taiwan, South Korea and the Philippines) and the US stock market. First, we find significant increases in the conditional correlations (contagion) in the first phase of the global financial crisis. Using the DCC-MGARCH model, we also reveal additional significant increases in the conditional correlations (herding) during the second phase of the global financial crisis. Second, by employing the DECO-MGARCH model, we confirm increasing equicorrelation (contagion and herding) in the nine sample markets during the two phases of the global financial crisis. Third, we apply the DCCX- and DECOX-MGARCH models and find that foreign investment, sovereign CDS premium, VIX index and TED spread are significant factors affecting emerging East Asian stock markets. Finally, we compare the accuracy of the conditional correlation estimates of DCC and DCCX (DECO and DECOX) models. We find that the DCCX (DECOX) model provides more accurate conditional correlation (equicorrelation) estimates than the DCC (DECO) model.

In Chapter 2 we offer two contributions. First, we employ the wavelet coherence analysis to analyze oil-stock interdependence. Additionally, we employ the recently developed wavelet coherence analysis, which exposes regions in terms of the degree and direction (in phase or out phase) of co-movement and simultaneously reveals the effect-result relationship in time-frequency space. Second, we measure the oil-stock portfolio diversification benefits. We find that the independence between oil and stock returns for East Asian countries is almost homogenous while China and Japan have a weaker correlation with oil prices compared to other East Asian countries. The average coherency values are relatively higher in the crisis sub-periods of 1997 to 2001 and 2007 to 2011, implying that the oil and East Asian stock markets experienced contagion effect during the global financial crisis period. Additionally, we find that oil and stock returns move in phase at all frequencies and oil prices lead to stock returns in the long-run cycle. Finally, from a financial perspective, the values of downside risk reduction are higher than zero in the high frequencies and negative in the low frequencies for all East Asian stock markets, which implies that the oil-stock portfolio can reduce the downside risk in the short term and provides evidence that the benefits of oil-stock portfolio diversification reduced over the long term horizon for East Asian markets. Our findings suggest that for long-term investors, relatively high strength of co-movement in the long term reduces the diversification benefit between the involved assets while, for short-term investors, investment in crude oil is a good choice because of the low degree of correlation with stock returns; investors should only be concerned with increased co-movements during the crisis period, which suggests a high risk of contagion. For East Asian policy makers, understanding the relationships between oil prices and stock returns when they are leading or lagging can help governments devise sound policy measures to avoid financial market risk

In Chapter 3 we investigate the interdependence between East Asian stock markets and the prices of crude oil and gold. Our application is firstly based on an AR-GARCH type process for marginal distribution. Second, the obtained standardized residuals for each variable are decomposed up to 6 levels, covering the short-term, midterm, and long-term horizons. Finally, we employ the conditional copula functions to capture the interdependence between assets over different time scales. We summarize our results as follows: Most interdependence between oil and East Asian stock markets is positive and weak in the original series and it varies and increases as time scales increase. The gold and East Asian stock interdependence is always weaker than those of oil-stock pairs. Similar with the interdependence estimates, the tail dependence sharply increased in the long term horizon. Generally, empirical results provide strong evidence that interdependence between East Asian stock markets and the prices of oil and gold varies across different horizons. Our empirical results have implications for heterogeneous investors and market participants. Relatively low strength of interdependence and lower tail dependence between East Asian stock markets and the prices of oil and gold means that crude oil or gold is good choices to diversify risk in the short-term.

Chapter 1

Dynamic correlation and equicorrelation analysis of global financial turmoil: evidence from emerging East Asian stock markets

1.1 Introduction

The global financial crisis that began in 2007 with the collapse of the subprime market in the US has led to considerable turmoil, affecting economies all over the world. A large number of emerging markets, such as those of the emerging East Asian countries, have suffered particularly sharp losses. Notably, in the first phase of the global financial crisis, which began with the failure of Lehman Brothers in September 2008 (Min and Hwang 2012), stock markets worldwide experienced substantial asset price declines and entered a period of high volatility. Dooley and Hutchison (2009) show that the bankruptcy of Lehman Brothers in September 2008 generated a direct financial shock to emerging markets. Emerging East Asian stock markets were no exception, with volatility in these markets increasing significantly during this period (Yiu, Ho, and Choi 2010). It seems that the wave of shocks experienced by these markets originated from the US stock market.

The study of financial contagion is popular as such financial crises have had increasingly large global effects. For instance, many studies report contagion in both emerging markets (Cho and Parhizgari 2008; Dooley and Hutchison 2009; Kim and Kim 2011) and advanced markets (Boyson, Stahel, and Stulz 2010; Chudick and Fratzscher

2011; Min and Hwang 2012). However, previous studies have failed to reach a consensus on the existence of contagion with the earlier financial crisis. Forbes and Rigobon (2002) investigate structural breaks in correlations between markets after making proper adjustments for heteroscedasticity. Diebold and Yilmaz (2007) measure linkages in asset returns and return volatilities and find evidence of episodes of contagion. In other words, it is important to consider heteroscedasticity and dynamic correlation to make appropriate adjustments for stock market contagion.

The present study analyses contagion from the US stock market to the financial markets in the eight emerging East Asian countries, namely Hong Kong, Thailand, Malaysia, Singapore, Indonesia, Taiwan, South Korea and the Philippines, during the recent global financial crisis. We investigate these emerging East Asian financial markets for several reasons. First, over the past several decades, East Asia has shown remarkable economic progress and has had an increasing impact on the world economy (Drysdale and Armstrong 2010), to the point that the emergence of these economies is changing the landscape of the global economy. Second, since the 1997 Asian crisis, East Asian countries have accelerated efforts at regional financial cooperation and integration (Boubakri and Guillaumin 2015). In particular, the inter-regional economies of emerging East Asian countries are becoming increasingly interdependent. Pontines and Siregar (2009) revisit the period around the time of the Asian financial crisis using daily stock exchange data of eight emerging East Asian countries. However, few studies test whether there was a significant break in the emerging East Asian stock markets during such global financial crisis periods. Further, China is one of the most influential economies among the East Asian countries; however, its stock markets are not yet fully accessible to foreign trade on account of the limitations imposed by the Mainland Chinese government (Kim and Kim 2011). Therefore, it would be interesting to investigate whether there is evidence of contagion from the US financial market to its emerging East Asian counterparts.

Many previous studies adopt the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002) to estimate dynamic correlations between sample countries while investigating financial contagion. For example, Cho and Parhizgari (2008) apply the DCC model to analyse the equity markets of eight countries during the 1997 East

Asian financial crisis and find contagion across all 14 pairs of source–target countries. Yiu, Ho, and Choi (2010) employ the asymmetric DCC model to estimate the correlation between the Asian factor and the US stock market, and while they discover contagion in the estimated dynamic correlations from late 2007 onwards, there is no evidence of contagion between the US and individual Asian markets during the Asian financial crisis. Min and Hwang (2012) analyse the DCCs of the daily stock returns between four OECD countries and the US for the period 2006–2010 and find evidence of contagion and herding effects during the global financial crisis. In this article, we analyse the equicorrelation of the US stock market using the recent Dynamic Equicorrelation-Multivariate Generalized Autoregressive Conditional Heteroscedasticity (DECO-MGARCH) model proposed by Engle and Kelly (2012). The DECO-MGARCH model is an advanced case of the DCC model of Engle (2002) and can be interpreted in three- and higher dimensional systems. It is important to estimate high-dimensional matrices of assets in terms of risk management. The original business-oriented contributions are that it allows the estimated conditional correlations by assuming some reasonable hypothesis (e.g. the correlation is equal across markets at any given time) and that it varies over time. Aboura and Chevallier (2013) provide the first empirical application of the DECO model to a cross-market data set composed of equities, bonds, foreign exchange and commodity returns during 1983–2013. While examining the role of trading volumes in GARCH-based tests of the Mixture of Distributions Hypothesis on firm-level data for the 20 largest Fortune 500 stocks, Carroll and Kearney (2012) examine the short-term dynamics, macroeconomic sensitivities and longer-term trends in the variances and covariances of daily stock returns for the Eurozone, and in doing so, apply various Autoregressive (AR)-GARCH models and culminate with the DECO-GARCH model. Connor and Suurlaht (2013) modify the Mixed Data Sampling DCC-GARCH model to include a scalar measure of the degree of correlation in dynamic correlation matrices.

Our examination differs from the study of Min and Hwang (2012), in that we compare the DCC-MGARCH model with the DECO-MGARCH model, to analyse contagion during the global financial crisis, while Min and Hwang (2012) only consider the bivariate correlation based on the DCC-MGARCH model. Moreover, we are interested in finding the channels of the transmission mechanisms in emerging East Asian and US stock markets. In this study, we employ the new DCC-MGARCH model with Exogenous Variables (called DCCX-MGARCH), as proposed by Min and Hwang (2012). We propose an advanced version of the DECO-MGARCH model with Exogenous Variables (DECOX-MGARCH), which can estimate both the conditional correlation (equicorrelation) and the effects of the explanatory variables simultaneously in one framework. A large number of variables can be considered as relevant economic factors determining DCCs and equicorrelation. We choose foreign investment, the sovereign credit default swap (CDS) spread, the VIX index and the TED spread as the exogenous economic variables. We use the amount of foreign investment to measure the financial interdependence of local stock markets. We also include the sovereign CDS spread as a macroeconomic factor and a measure of country risk (Longstaff et al. 2011) of emerging East Asian economies. The VIX index, the volatility index issued by the Chicago Board Options Exchange, is considered to be an observation of market uncertainty (Gonzalez-Hermosillo and Hesse 2009). The TED spread, defined by the difference between the interest rates on Libor and US Treasury bills, is included to consider the effect of liquidity risk (Brunnermeier and Pedersen 2009) on the conditional correlations and equicorrelation. Moreover, to extend their study, we consider using the MSE loss function to evaluate the conditional correlations estimated by DCC and DCCX models, as well as the equicorrelation estimated by DECO and DECOX models.

Our contribution can be summarized as follows. First, we analyse dynamic conditional equicorrelation between nine stock marketing by applying the recently proposed DECO model. Second, we employ the advanced DCCX model and the DECOX model to identify the channels of contagion. Finally, we find that the exogenous variables in DCCX and DECOX models are significant. More accurate conditional correlation and equicorrelation estimates are provided by incorporating exogenous variables in DCC and DECO models.

The rest of this paper is organized as follows. Section 2 reviews the econometric methods applied in this study. Section 3 describes our data set and descriptive statistics.

Section 4 presents our empirical results. Section 5 concludes the paper.

1.2 Model Specification

In this section, we first discuss the specification of the DCC-MGARCH model and the DECO-MGARCH model. Second, we specify the DCCX and DECOX models to estimate the impact of the exogenous variables on the conditional correlations and equicorrelation.

1.2.1 DCC-MGARCH model

Consider y_t for the t = 1,…,T asset returns series. The AR (1)-GARCH (1, 1)[1] is given as follows:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{USA} + \varepsilon_t = \mu_t + \varepsilon_t \qquad (1.1)$$

$$\varepsilon_t | \mathcal{F}_{t-1} = h_t^{1/2} z_t \qquad (1.2)$$

where y_t is decomposed into a conditional mean (μ_t) and a conditional variance (ε_t). Then,$\varepsilon_t|\mathcal{F}_{t-1}$is defined as the product of conditional volatility ($h_t^{1/2}$) and a standardized residual (z_t) with some information set $\mathcal{F}_{t-1}$. ϕ_0, ϕ_1 and ϕ_2 are the parameters to be estimated. The parameter ϕ_2 measures the effects of US stock returns on the stock

[1] We select the lag of AR-GARCH model according to the results of the Bayesian information criterion test.

returns of the emerging East Asian markets.

The Gaussian GARCH model cannot explain the leptokurtosis exhibited by stock returns in this study. Bollerslev (1987) suggests replacing the conditional normal distribution with the conditional Student's *t*-distribution. The distribution of the error term (ε_t) according to Bollerslev (1987) takes the form

$$f(\varepsilon_t) = \frac{\Gamma[\frac{1+v}{2}]}{\sqrt{v\pi}\,\Gamma(\frac{v}{2})}[1 + \frac{{\varepsilon_t}^2}{v}]^{-\frac{1+v}{2}} \tag{1.3}$$

where v is the degrees of freedom of the *t*-distribution.

$$h_{i,t} = \omega_i + \beta_i h_{i,t-1} + \alpha_i {\varepsilon_{i,t-1}}^2, i = 1, \ldots, 5 \tag{1.4}$$

where the dynamics of volatility ($h_{i,t}$) use the GARCH (1, 1) model. ω, α and β are the parameters to be estimated. The parameter β measures the persistence in conditional volatility.

We calculate the DCCs from the conditional covariance matrix based on Equation 4:

$$H_t = D_t R_t D_t \tag{1.5}$$

$$D_t = diag\left({h_{1,t}}^{\frac{1}{2}}, \ldots, {h_{n,t}}^{\frac{1}{2}}\right) \tag{1.6}$$

where H_t is an $N \times N$ positive definite matrix, such that H_t is the conditional variance matrix of y_t by the volatilities $h_{i,t}$. D_t is an $N \times N$ diagonal matrix of the SDs of the residual returns.

$$R_t{}^{DCC} = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{1.7}$$

$$Q_t{}^{DCC} = (\bar{Q}^{DCC} - A'\bar{Q}^{DCC} A - B'\bar{Q}^{DCC} B) + A' z_{t-1} z'_{t-1} \mathrm{A} + B' Q_{t-1}{}^{DCC} B \tag{1.8}$$

$$\bar{Q}^{DCC} = T^{-1} \sum_{t=1}^{T} z_t z'_t \tag{1.9}$$

where $R_t{}^{DCC}$ is the correlation matrix constituted by the correlations $\rho_{ij,t}$. In order to parameterize the correlation coefficient ρ_t, it is assumed that $Q_t{}^{DCC}$ is an autoregressive process. $\bar{Q}^{DCC}$ is the $N \times N$ unconditional correlation coefficient matrix. The $z_{t-1} z'_{t-1}$ lagged function of the standardized residuals is derived from the univariate GARCH estimation. *A* and *B* are diagonal matrices.

The scalar DCC is

$$Q_t{}^{DCC} = (\bar{Q}^{DCC} - a_1 \bar{Q}^{DCC} - b_1 \bar{Q}^{DCC}) + a_1 z_{t-1} z'_{t-1} + b_1 Q_{t-1}{}^{DCC} \tag{1.10}$$

with $a_1, b_1 \geq 0$. For this model, the parameter b_1 represents the degree of inertia in the time-varying conditional correlations, while the parameter a_1 represents the degree of perturbation to $\rho_{ij,t}$.

The following condition is a necessary and sufficient condition for $Q_t{}^{DCC}$ to be positive definite:

$$a_1 + b_1 < 1 \tag{1.11}$$

We write the correlation coefficient in the bivariate case:

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} = \frac{(1-a-b)\bar{q}_{12} + az_{1,t-1}z_{2,t-1} + bq_{12,t-1}}{\sqrt{[(1-a-b)\bar{q}_{11} + az^2{}_{1,t-1} + bq_{11,t-1}][(1-a-b)\bar{q}_{22} + az^2{}_{2,t-1} + bq_{22,t-1}]}} \tag{1.12}$$

1.2.2 DECO-MGARCH model

We use the DECO-MGARCH model introduced by Engle and Kelly (2012) to describe the dynamic equicorrelation of the eight emerging East Asian stock markets and the US stock market. The dynamic equicorrealtion model can be specified as:

$$R_t{}^{DECO} = (1 - \bar{\rho_t})I_n + \bar{\rho_t}J_{n\times n} \tag{1.13}$$

$$\bar{\rho_t} = \frac{2}{n(n-1)}\sum_{i\neq j}\rho_{ij,t} = \frac{2}{n(n-1)}\sum_{i\neq j}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}, i,j = 1,2,\dots,n$$

(1.14)

$$Q_t{}^{DECO} = (\bar{Q}^{DECO} - a_2\bar{Q}^{DECO} - b_2\bar{Q}^{DECO}) + a_2z_{t-1}z'{}_{t-1} + b_2Q_{t-1}{}^{DECO} \tag{1.15}$$

where I_n denotes the n-dimensional identity matrix, and $J_{n\times n}$ is the $n \times n$ matrix of ones. $\overline{\rho_t}$ is the equicorrelation, which can be calculated as the average of the $\frac{2}{n(n-1)}$ dynamic correlations at time t, implying the equicorrelation represents the mean of conditional correlations. $q_{ij,t}$ is the ij element of Q_t^{DECO} in Equation (1.15).

The DECO-MGARCH model is needed to estimate the high-dimensional matrices of assets in terms of risk management. It allows us to estimate the conditional equicorrelations by assuming that the correlation is equal across markets at any given time and varies in time. By estimating the dynamic conditional equicorrelation, we investigate the contagion effect from the US stock market to the emerging East Asian stock markets during the global financial crisis.

1.2.3 Estimation

The DCC- and DECO-MGARCH model parameters can be estimated by quasi-maximum likelihood. The log-likelihood function is

$$\mathcal{L}^{DCC}(\theta) = [-1/2\sum_{t=1}^{T}\left(nlog(2\pi) + 2\log|D_t| + \varepsilon_t' D_t^{-2}\varepsilon_t\right)] + [-1/2\sum_{t=1}^{T}\left(\log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t' \varepsilon_t\right) \tag{1.16}$$

$$\mathcal{L}^{DECO}(\theta) = -1/T\sum_{t=1}^{T}\left(\log|R_t^{DECO}| + \varepsilon_t' {R_t^{DECO}}^{-1}\varepsilon_t\right) \tag{1.17}$$

1.2.4 DCCX and DECOX models

In this subsection, we specify the DCCX and DECOX models in which the conditional correlation and equicorrelation are estimated by incorporating exogenous variables. The main purpose of this specification is to identify the exogenous global factors that may influence the dynamic behaviour of the conditional correaltion and equicorrelation.

$$h_{12t} = \rho(X_t)\sqrt{h_{11,t}\, h_{22,t}} \tag{1.18}$$

where $-1 < \rho(X_t) < 1$ is a monotonic increasing function of X_t, a $k \times 1$ vector of the economic fundamental variables that may affect the magnitude of the conditional correlations and equicorrelation. The DCCX and DECOX models are promising tools that help identify the propagation channel of comovements among these stock markets.

With reference to Min and Hwang (2012), we use the following parameterization for this conditional correlation function:

$$\rho(X_t) = 2\left[\frac{\exp(\gamma' X_t)}{1+\exp(\gamma' X_t)}\right] - 1 \tag{1.19}$$

where $X_t = [x_1, x_2, \dots x_k, DM_1, DM_2]'$, while $\gamma = [\gamma_0, \gamma_1, \dots \gamma_{k+2}]'$ is a vector of the coefficients that measures the effect of X_t on the conditional correlations and equicorrelation. This parameterization allows $\rho(X_t)$ to be bounded below and above by -1 and 1, respectively and thereby provides an appropriate specification for the conditional correlations and equicorrelation. We use foreign investment, sovereign CDS premium, VIX index and TED spread as exogenous variables, which are supposed to influence the conditional correlations and equicorrelation.

An important issue in analysing the global financial crisis is to understand the chronology of the events that make up the crisis (Mun and Brooks 2012). Bartram and Bodnar (2009) construct a chronology of the financial crisis from 2007–2009. Dooley and

Hutchinson (2009) divide the timeline of the global crisis into three periods they call ‘pre-crisis’, ‘crisis point’ (the Lehman bankruptcy) and ‘post-crisis’. Examples of events analysed include bankruptcies (including the Lehman Brothers bankruptcy), write downs, US political events and positive and negative economic developments in the US, among others. Similarly, Min and Hwang (2012) use the chronology of the financial crisis outlined in Dooley and Hutchinson (2009) to create two additional sub-phases: the first and the second phases of the crisis. In this paper, our sub-phase periods reflect the phases devised by Min and Hwang (2012), and we add our data in the fourth phase. Thus, our sub-phases include: Phase 1 (the pre-crisis period, spanning 1 December 2006 to 14 September 2008), Phase 2 (the first phase of the crisis period, spanning 15 September 2008 to 14 September 2009, Phase 3 (the second phase of the crisis period, spanning 15 September 2009 to 31 December 2011) and the Post-crisis period (spanning 1 January 2012 to 28 February 2014). DM_1 and DM_2 are dummy variables for the first (15 September 2008 to 14 September 2009) and second phase (15 September 2009 to 30 December 2011) of the crisis period, respectively.

1.3 Data and Descriptive Statistics

The data used in this study are the daily stock returns from 1 December 2006 to 28 February 2014 of the eight emerging East Asian stock markets and the US stock market, all of which were seriously affected by the global financial crisis. The data set consists of the stock indices of Hong Kong (Hang Seng Index), Thailand (Bangkok SET Index), Malaysia (Kuala Lumpur SE Index), Singapore (Singapore SE Index), Indonesia (Jakarta SE Composite Index), Taiwan (TWSE Index), South Korea (Korea SE Composite Index), the Philippines (Philippine SE Index) and the US (S&P500 Index). The returns of the stock indices are computed as 100 times the first difference in the log of the data.

Table 1.1 shows the descriptive statistics for the stock market returns of the emerging East Asian countries and the US. Panel A of Table 1.1 shows that average daily stock market returns are positive for the whole sample period. Panels B–E of Table 1.1 show that both daily returns and their SDs are generally highest in the first phase of the crisis period, followed by the second phase. The values of skewness and kurtosis suggest that there are heavier tails and larger peaks than a normal distribution would have. The Jarque–Bera statistics that are significant at 1% indicate that we can reject the hypothesis that all daily return series have normal distributions. Therefore, we use the Student's *t*-distribution to model the univariate GARCH process. In addition, the statistics of the ARCH–Lagrange Multiplier (LM) test reject the null hypothesis of no ARCH effect for all countries, and the Ljung–Box *Q* test statistics reject the null hypothesis of no serial correlation for all countries for the whole sample period.

Insert Table 1.1 here

Fig. 1.1 shows the daily stock returns during the period December 2006–February 2014. Fig. 1.1 and Table 1.1 show that the Hong Kong stock market shows the highest volatility (as high as 1.757) of all emerging East Asian stock markets, and Malaysia, the lowest (as low as 0.925). Moreover, the volatility of all stock markets increases significantly after 15 September 2008 (the first phase of the global financial crisis). Table 1.2 presents the unconditional correlation matrix. We note that the degrees of correlation between the emerging East Asian stock markets and the US market are highest during the first phase of the crisis, followed by the second phase.

Insert Table 1.2 here

Insert Figure 1.1 here

We include daily amounts of foreign investment, sovereign CDS premium, VIX index and TED spread as exogenous variables that determine the conditional correlations and equicorrelation of the stock returns. We use the amount of foreign investment following Kim and Kim (2011), who shows that foreign order flows denote the high dependence of local stock markets in emerging Asian countries on the trade patterns of foreign investors, which are significant factors affecting foreign exchange markets. We also include the sovereign CDS spread as a macroeconomic factor and a measure of country risk (Longstaff et al. 2011) of emerging East Asian economies. Bystrom (2005) and Min and Hwang (2012) find that a high CDS spread increases stock price volatility. The VIX index is included as an observation of market uncertainty (Gonzalez-Hermosillo and Hesse 2009) since Giot (2005) shows that the VIX index and stock returns have a negative relationship. The TED spread, defined by the difference between the interest rates on Libor and US Treasury bills, is included to consider the effect of liquidity risk (Brunnermeier and Pedersen 2009) on the conditional correlations and equicorrelation. Lashgari (2000) and Cheung, Fung, and Tsai (2010) show that a higher TED spread implies tighter liquidity in the economy. Table 1.3 summarizes the statistical properties of the exogenous variables. All data are obtained from DataStream.

Insert Table 1.3 here

1.4 Empirical Results

1.4.1 Estimates of the DCC-MGARCH and DECO-MGARCH specifications

Table 1.4 presents the estimation results of the mean, conditional variance, conditional correlation and conditional equicorrelation equations. The results of the mean equation model show that the effects (ϕ_2) of the US stock market on the emerging East Asian countries are highly significant at the 1% level. This result is consistent with that of Kim and Kim (2011) in terms of the presence of spillover effects from the US to emerging East Asian stock markets. The variance equation model of Table 1.4 first suggests that all the coefficients of the conditional variance term (β) are close to 1 and statistically significant at the 1% level, implying high persistence (Chiang, Jeon, and Li 2007). Second, all the sums of the constant term (α) and the variance term (β) are less than 1, which indicates that the GARCH (1, 1) model fits the data well. Moreover, the degrees of freedom (v) of the Student's *t*-distributions are all significant at the 1% level, suggesting that the tails of the error terms (ϵ_t) are heavier than those of the normal distribution. Thus, using the Student's *t*-distribution to deal with these properties is appropriate. The results of the conditional correlation and equicorrelation equations indicate that all the parameters of the conditional variance (b_1) are statistically significant at the 1% level, indicating the high persistence of the conditional correlations and equicorrelation. Moreover, the sums of a_1 and b_1 are less than 1 and round off to 1, indicating that the DCC and DECO parameters lie within the range of typical estimates from the GARCH model.

Insert Table 1.4 here

Fig. 1.2 shows the conditional correlations and equicorrelation of the stock returns during the whole sample period. We can see that both the conditional correlations and equicorrelation increase after September 2008 (the first phase of the global financial crisis) and then become higher and persistent for a long time.

Table 1.5 reports the descriptive statistics of the conditional correlations and equicorrelation. This table shows that for the entire period, the mean value of the equicorrelation is very high (about 0.404). The mean value of the conditional correlation is highest for Korea (0.404) and lowest for the Philippines (0.051). From Panels B–E of Table 1.5, we can conclude that all the mean values of the conditional correlations and equicorrelation increased in the global financial crisis period, which is consistent with the findings noted in Table 1.2.

Insert Table 1.5 here

Insert Figure 1.2 here

1.4.2 Empirical results for the DCCX and DECOX models

Table 1.6 reports the estimation results for the DCCX and DECOX models. First, foreign investment has no effect on the conditional correlations for two countries. Second, sovereign CDS premium has a significant effect on the conditional correlations for all countries, but only Korea has a positive sign, which means that the increased sovereign risk measured by the CDS spread improves the correlation between the US and Korean stock markets. This finding is consistent with that of Bystrom (2005), who finds that an increase in stock price volatility is positively correlated with the CDS spread. Third, the VIX index has a significant positive effect on both the conditional correlations and the equicorrelation, implying that uncertainty in the US stock markets may have spread to these countries and the whole of the East Asian region. This finding is consistent with the previous estimates in Table 1.4, where all the estimations of b in the DCC and DECO models are positive and significant, implying significant conditional correlation and equicorrelation volatility contagion in these countries. Cai, Chou, and Li (2009) reveal that higher correlations emerge between stock markets experiencing higher volatility. Finally, an increased TED spread decreases the conditional correlations for six countries. Lashgari (2000) and Cheung, Fung, and Tsai (2010) show that a higher TED spread implies tighter liquidity in the economy. Therefore, worsening liquidity may decrease the conditional correlation of stock returns. Our finding is similar to that of Min and Hwang (2012), who show that an increased TED spread decreases the conditional correlations for OECD countries. Table 1.6 shows that most of the dummy variables are significant and positive.

Insert Table 1.6 here

1.4.3 Evaluation

We consider a mean squared error (MSE) loss function for comparing the accuracy of conditional correlation estimates of the DCC- and DCCX-MGARCH models.

$$\mathrm{MSE}(\hat{\rho}_t) = \frac{1}{T}\sum_{t=1}^{T}(\hat{\rho}_t - \rho_t)^2 \tag{1.20}$$

where $\hat{\rho}_t$ are the conditional correlations estimated by the DCC- and DCCX-MGARCH models, and ρ_t are the true correlations. Since the true correlations cannot be observed, a proxy is needed. Here, we approximate the true correlations by calculating unconditional correlations using the rolling window method. To check robustness, we use window sizes of 250, 300, 350 and 400 days.

We also calculate an MSE loss function for comparing the estimations of the DECO- and DECOX-MGARCH models. The MSE loss function of the DECO- and DECOX-MGARCH models is defined as follows:

$$\mathrm{MSE}(\hat{\rho}_t^{\;DECO}) = \frac{1}{T}\sum_{t=1}^{T}(\hat{\rho}_t^{\;DECO} - \bar{\rho}_t)^2 \tag{1.21}$$

where $\hat{\rho}_t^{DECO}$ is the conditional equicorrelation estimated by the DECO- and DECOX-MGARCH model, and $\overline{\rho_t}$ is the true equicorrelation approximated by averaging the eight cross-market rolling window correlations at time *t*. We also calculate the 250, 300, 350 and 400-day rolling window equicorrelations for comparison.

Tables 1.7 and 1.8 compare the conditional correlations estimated by the DCC and DCCX models and the conditional equicorrelation estimated by the DECO and DECOX models. We can see that the MSE values of the DCCX (DECOX) model are smaller than those of the DCC (DECO) model, implying that the conditional correlations (equicorrelation) estimates of the DCCX (DECOX) model are more accurate than those of the DCC (DECO) model. The result suggests that the DCCX (DECOX) model is better than the DCC (DECO) model. It is necessary to consider the impacts of exogenous variables. Fig. 1.2 shows that the dynamic conditional correlations (and equicorrelation) estimated by the DCC (and DECO) model (black line) are fluctuate, while those estimated by the DCCX (DECOX) model (blue line) and the true time-varying correlations (equicorrelation) approximated by the unconditional correlations are smooth at the sample periods. This implies that the dynamic conditional correlations (equicorrelation) estimations of the DCCX (DECOX) model are more consistent with the true time-varying correlations (equicorrelation) than those of DCC (DECO) model. These results are in agreement with the findings listed in Tables 1.7 and 1.8.

Insert Tables 1.7 and 1.8 here

1.5 Conclusion

In this paper, we investigate financial markets contagion between United States and eight East Asian emerging markets. We employed two types of models, the DCC-MGARCH and DECO-MGARCH models. The DCC-MGARCH model considers the conditional correlations between the emerging East Asian stock markets (Hong Kong, Thailand, Malaysia, Singapore, Indonesia, Taiwan, South Korea and the Philippines) and the US stock market, while the DECO-MGARCH model identifies the dynamic conditional equicorrelation among the nine sample countries. We also employ the DCCX- and DECOX-MGARCH models to investigate the main economic factors influencing the size of the conditional correlations and equicorrelation. Finally, we compare the accuracy of the conditional correlation estimates of the DCC and DCCX (DECO and DECOX) models by constructing MSE loss function.

Our empirical results can be summarized as follows. First, we find significant increases in the conditional correlations (contagion) in the first phase of the global financial crisis. Using the DCC-MGARCH model, we also reveal additional significant increases in the conditional correlations (herding) during the second phase of the global financial crisis. Second, by employing the DECO-MGARCH model, we confirm increasing equicorrelation (contagion and herding) in the nine sample markets during the two phases of the global financial crisis. Third, we apply the DCCX- and DECOX-MGARCH models, as they allow simultaneous estimation of the conditional correlation and equicorrelation coefficients and can be used to identify channels of contagion. We find that foreign investment, sovereign CDS premium, VIX index and TED spread are significant factors affecting emerging East Asian stock markets. An increased TED spread decreases the conditional correlations for six countries. The sovereign CDS premium has a significant effect on the conditional correlations, whereas the VIX index has a significant positive effect on both the conditional correlations and the equicorrelation. However, the impacts of foreign investment on the conditional correlations are limited. Finally, we compare the accuracy of the conditional correlation estimates of DCC and DCCX (DECO and DECOX) models by constructing MSE loss function. We find that the DCCX (DECOX) model provides more accurate conditional correlation (equicorrelation) estimates than the DCC (DECO) model.

Our results have a number of implications for investors and governments in emerging East Asian countries. The correlations estimated in this study are crucial inputs for international portfolio management and risk assessment, and understanding the changes in the conditional correlations and equicorrelation is important for international investments. Moreover, this approach can provide useful policy implications when policymakers wish to identify the global economic factors affecting the sign and size of the conditional correlations and equicorrelation. Our empirical results imply that the emerging East Asian countries are quite vulnerable to external shocks. Thus, this possibility calls for a need to construct a financial stabilization mechanism against contagion.

Table 1.1. Descriptive statistics for stock market returns

	Hong Kong	Thailand	Malaysia	Singapore	Indonesia	Taiwan	Korea	Philippine	United States
Panel A. Entire period, 2006/12/1–2014/2/28									
N	1890	1890	1890	1890	1890	1890	1890	1890	1890
Mean ($\times 10^{-2}$)	1.06	3.074	3.427	0.117	5.183	0.504	1.705	4.416	1.514
S.D.	1.757	1.446	0.925	1.358	1.504	1.324	1.449	1.389	1.432
Normality test									
Skewness	0.068	-1.096	-0.659	-0.179	-0.64	-0.37	-0.564	-0.839	-0.31
Kurtosis	8.11	14.563	7.761	5.539	7.11	3.305	8.168	8.798	9.201
JB test	5181.5***	17061***	4880.7***	2426.3***	4119***	903.5***	5355.4***	6318.8***	6697***
Heteroscedasticity test									
ARCH LM test	442.1***	201.2***	188.9***	479.5***	211***	195.4***	431.9***	178.27***	444.7***
Autocorrelation test									
Q (20)	36.4**	47.8***	64.6***	74.2***	73.1***	64.6***	69.995***	89.551***	88.5***
Panel B. Pre-crisis period, 2006/12/1–2008/9/14									
N	465	465	465	465	465	465	465	465	465
Mean ($\times 10^{-2}$)	0.748	-2.685	-0.73	-1.959	0.842	-4.476	0.642	-2.035	-2.357
S.D.	1.88	1.529	1.138	1.462	1.603	1.493	1.423	1.529	1.126
Normality test									
Skewness	-0.043	-1.682	-1.78	-0.188	-0.597	-0.456	-0.403	-0.313	-0.211
Kurtosis	6.347	32.927	16.447	4.581	7.049	4.945	2.432	5.297	4.261
JB test	217.2***	17573***	3749.2***	51.1***	345.384***	89.5***	127.532***	552.56***	34.274***

Heteroscedasticity test									
ARCH LM test	77.5***	66.1***	13.9***	50.1***	88.378***	36.48***	33.73***	33.287***	14.295**
Autocorrelation test									
Q (20)	20.1	27.3	24.6	17.3	22.91	31.7***	29.151	30.077	33.589**
Panel C. The first phase of the crisis period, 2008/9/15–2009/9/14									
N	260	260	260	260	260	260	260	260	260
Mean ($\times 10^{-2}$)	3.017	2.989	5.922	1.391	12.551	6.902	3.867	3.867	-4.925
S.D.	3.12	2.194	1.091	2.465	2.3	2.021	2.494	2.494	2.78
Normality test									
Skewness	0.166	-0.962	-0.021	-0.061	-0.539	-0.148	-0.509	-0.510	-0.093
Kurtosis	6.132	7.768	4.726	4.353	7.38	4.116	4.231	4.232	5.365
JB test	107.518***	286.474***	32.299***	19.997***	220.459***	14.46***	206.07***	206.071**	61.018***
Heteroscedasticity test									
ARCH LM test	56.102***	34.143***	45.574***	52.721***	29.065***	13.56**	64.016***	25.919***	42.720***
Autocorrelation test									
Q (20)	22.423	29.191*	30.749*	32.885**	45.648***	25.31	40.92	29.833*	28.41
Panel D. The second phase of the crisis period, 2009/9/15–2011/12/30									
N	599	599	599	599	599	599	599	599	599
Mean ($\times 10^{-2}$)	2.072	6.307	3.966	-0.773	7.641	-0.747	1.843	1.843	2.975
S.D.	1.373	1.265	0.603	1.026	1.307	1.165	1.296	1.296	1.258
Normality test									
Skewness	-0.324	-0.246	-0.378	-0.386	-0.801	-0.563	-0.570	-0.570	-0.449

Kurtosis	5.032	6.262	4.854	4.105	10.083	5.27	3.003	3.003	6.19
JB test	113.476***	271.252***	99.989***	45.353***	1314.328***	159.9***	257.532***	257.53***	273.727***
Heteroscedasticity test									
ARCH LM test	38.413***	41.189***	68.074***	40.712***	39.107***	26.76***	71.506***	57.427***	114.263***
Autocorrelation test									
Q (20)	14.95	31.078*	27.227	12.48	30.026*	40.7***	54.764*	47.515***	38.838***
Panel E. Post-crisis period, 2012/1/1-2014/2/28									
N	564	564	564	564	564	564	564	564	564
Mean $\times 10^{-2}$	3.797	4.55	3.407	2.787	3.423	3.818	1.435	6.814	6.934
S.D.	0.984	1.078	0.53	0.695	1.084	0.823	0.847	1.160	0.741
Normality test									
Skewness	-0.078	-0.442	-0.1	-0.207	-0.388	-0.15	0.003	-0.853	-0.197
Kurtosis	3.931	6.017	11.31	4.123	6.325	4.33	1.465	5.519	4.26
JB test	20.92***	232.2***	1623***	33.69***	273.9***	43.69***	50.579***	785.81***	40.99***
Heteroscedasticity test									
ARCH LM test	14.5**	53.98***	27.36***	30.38***	53.39***	16.94***	31.459***	71.22***	12.14**
Autocorrelation test									
Q (20)	16.69	21.86	38.24***	37.92***	37.53**	23.63	46.29	48.815***	13.87

Notes: N is the sample size and S.D. stands for standard deviation. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; JB test corresponds to the Jarque–Bera test statistics, Q (20) is the Ljung–Box Q statistics for the null hypothesis that there is no autocorrelation up to order 20 for standardized residuals.

Table 1.2. Unconditional correlation matrix

	Hong Kong	Thailand	Malaysia	Singapore	Indonesia	Taiwan	Korea	Philippine	United States
Panel A. Entire period, 2006/12/1–2014/2/28									
Hong Kong	1								
Thailand	0.547	1							
Malaysia	0.480	0.421	1						
Singapore	0.753	0.554	0.528	1					
Indonesia	0.597	0.521	0.509	0.617	1				
Taiwan	0.601	0.410	0.473	0.567	0.519	1			
Korea	0.675	0.449	0.475	0.641	0.520	0.695	1		
Philippine	0.444	0.368	0.457	0.370	0.458	0.445	0.414	1	
United States	0.241	0.224	0.104	0.295	0.150	0.137	0.220	0.028	1
Panel B. Pre-crisis period, 2006/12/1–2008/9/14									
Hong Kong	1								
Thailand	0.425	1							
Malaysia	0.483	0.371	1						
Singapore	0.762	0.447	0.584	1					
Indonesia	0.658	0.413	0.511	0.641	1				
Taiwan	0.565	0.375	0.465	0.570	0.452	1			
Korea	0.666	0.425	0.501	0.662	0.521	0.712	1		
Philippine	0.431	0.202	0.469	0.385	0.393	0.409	0.449	1	
United States	0.050	0.051	0.074	0.127	0.107	0.054	0.093	0.002	1
Panel C. The first phase of the crisis period, 2008/9/15–2009/9/14									

Hong Kong	1								
Thailand	0.694	1							
Malaysia	0.522	0.535	1						
Singapore	0.781	0.689	0.566	1					
Indonesia	0.579	0.640	0.539	0.640	1				
Taiwan	0.620	0.472	0.526	0.562	0.606	1			
Korea	0.700	0.524	0.531	0.677	0.569	0.692	1		
Philippine	0.508	0.536	0.489	0.392	0.427	0.513	0.427	1	
United States	0.359	0.375	0.162	0.359	0.160	0.138	0.281	0.036	1

Panel D The second phase of the crisis period, 2009/9/15–2011/12/30

Hong Kong	1								
Thailand	0.541	1							
Malaysia	0.522	0.442	1						
Singapore	0.731	0.538	0.502	1					
Indonesia	0.638	0.518	0.551	0.640	1				
Taiwan	0.663	0.421	0.517	0.611	0.535	1			
Korea	0.669	0.432	0.485	0.598	0.510	0.728	1		
Philippine	0.433	0.329	0.442	0.322	0.436	0.428	0.396	1	
United States	0.194	0.164	0.082	0.330	0.170	0.211	0.221	-0.015	1

Panel E Post-crisis period, 2012/1/1-2014/2/28

Hong Kong	1				
Thailand	0.450	1			
Malaysia	0.301	0.297	1		
Singapore	0.652	0.472	0.294	1	
Indonesia	0.505	0.467	0.421	0.499	1

Taiwan	0.573	0.322	0.303	0.519	0.416	1			
Korea	0.632	0.344	0.274	0.560	0.436	0.643	1		
Philippine	0.385	0.389	0.403	0.389	0.466	0.417	0.406	1	
United States	0.211	0.171	0.038	0.262	0.144	0.121	0.202	0.085	1

Notes: All estimates are statistically significant at the level of 1%.

Table 1.3. Descriptive statistics for exogenous variables

	N	Mean	S.D.	Skewness	Kurtosis	JB test
VIX	1890	22.584	10.516	2.046	5.290	3523.1***
Foreign investment						
Taiwan	1785	43342316.59	16768192.087	1.168	3.144	1141.439***
Philippine	1759	5431271.295	11461715.997	32.667	1244.203	113.771e06***
Sovereign CDS spread						
Hong Kong	999	55.979	39.32	0.925	0.709	163.692***
Thailand	999	126.13	66.03	1.457	2.578	629.904***
Malaysia	999	106.705	70.343	1.152	1.510	315.966***
Singapore	999	64.232	40.421	0.656	-0.431	79.473***
Indonesia	999	299.142	172.117	2.219	5.348	2011.1***
Taiwan	704	83.121	3.297	0.475	-0.836	47.043***
South Korea	999	131.252	108.166	1.583	2.529	683.846***
Philippine	999	250.219	89.377	2.317	9.212	4426.049***
TED spread						
Hong Kong	1890	1.099	1.164	1.727	1.167	1167.87***
Thailand	1890	-0.652	1.698	0.669	-0.796	191.047***
Malaysia	1890	-1.023	1.831	0.941	-0.878	340.145***
Singapore	1890	1.369	1.623	1.201	-0.261	459.577***
Indonesia	1890	-4.156	2.327	1.127	1.476	578.879***
Taiwan	1890	1.128	1.421	1.044	-0.709	382.696***
South Korea	1890	-1.303	1.244	0.726	-0.844	222.350***
Philippine	1890	-2.699	1.347	0.769	-0.782	234.789***
United	1890	51.843	46.032	2.128	5.141	3507.872***

States

Notes: N is the sample size and S.D. stands for standard deviation. *** indicates significance at the 1% level. JB test corresponds to the Jarque–Bera test statistics.

Table 1.4. Empirical analysis results of the DCC- and DECO-MGARCH models

	Hong Kong	Thailand	Malaysia	Singapore	Indonesia	Taiwan	Korea	Philippine	United States
Mean equation $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{USA} + \varepsilon_t$									
ϕ_0	0.002	0.046*	0.023	-0.007	0.072***	0.072***	0.034	0.085***	0.033
	(0.024)	(0.025)	(0.021)	(0.018)	(0.023)	(0.023)	(0.024)	(0.025)	(0.017)
ϕ_1	-0.021**	-0.013	0.122***	-0.131***	-0.005	0.033**	0.002	0.123***	-0.196***
	(0.009)	(0.021)	(0.013)	(0.010)	(0.013)	(0.015)	(0.025)	(0.026)	(0.012)
ϕ_2	-0.018**	0.011	0.025**	-0.027***	0.102***	0.131***	0.212***	0.032	_
	(0.009)	(0.016)	(0.010)	(0.016)	(0.024)	(0.024)	(0.024)	(0.023)	
Variance equation $h_{i,t} = \omega + \beta_i h_{i,t-1} + \alpha_i \varepsilon_{i,t-1}{}^2, i = 1,\dots,n$									
ω	0.022**	0.054***	0.063**	0.005***	0.058***	0.007	0.016***	0.043***	0.033**
	(0.002)	(0.015)	(0.021)	(0.001)	(0.015)	(0.005)	(0.005)	(0.014)	(0.007)
α	0.071***	0.156***	0.106***	0.183***	0.154***	0.021***	0.079***	0.127***	0.15***
	(0.012)	(0.019)	(0.035)	(0.013)	(0.029)	(0.012)	(0.011)	(0.016)	(0.017)
β	0.912***	0.822***	0.84***	0.812***	0.823***	0.936***	0.913***	0.858***	0.823***
	(0.011)	(0.019)	(0.033)	(0.023)	(0.034)	(0.013)	(0.011)	(0.017)	(0.024)
v	6.017***	5.507***	4.349***	7.430***	5.102***	5.773***	5.521***	4.454***	4.442***
	(0.922)	(0.597)	(0.333)	(1.234)	(0.546)	(0.743)	(0.630)	(0.397)	(0.234)
Correlation equation $q_{ij,t}{}^{DCC} = (\bar{q}^{DCC} - a_1\bar{q}^{DCC} - b_1\bar{q}^{DCC}) + a_1 z_{ij,t-1} + b_1 q_{ij,t-1}{}^{DCC}$									
a_1			0.021***						
			(0.001)						
b_1			0.954***						
			(0.005)						
Log-likelihood			-24301.163						
Equicorrelation equation $q_{ij,t}{}^{DECO} = (\bar{q}^{DECO} - a_1\bar{q}^{DECO} - b_1\bar{q}^{DECO}) + a_1 z_{ij,t-1} + b_1 q_{ij,t-1}{}^{DECO}$									

a_1	0.024***
	(0.004)
b_1	0.967***
	(0.006)
Log-likelihood	-21578.518

Notes: The numbers in parentheses are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 1.5. Descriptive statistics of conditional correlations and equicorrelation

	DCC								DECO
	United States–Hong Kong	United States–Thailand	United States–Malaysia	United States–Singapore	United States–Indonesia	United States–Taiwan	United States–Korea	United States–Philippine	Seven sample markets
Panel A. Entire period, 2006/12/1–2014/2/28									
N	1890	1890	1890	1890	1890	1890	1890	1890	1890
Mean	0.193	0.171	0.105	0.254	0.150	0.124	0.404	0.051	0.404
S.D.	0.079	0.081	0.081	0.077	0.076	0.080	0.058	0.059	0.067
Skewness	-0.107	0.20	0.201	-0.382	-0.236	0.053	-0.290	-0.042	-0.253
Kurtosis	-0.671	0.045	0.109	-0.503	-0.182	-0.502	-0.478	-0.041	-0.555
JB test	39.08***	0.286	13.71***	65.96***	20.129***	20.739***	44.417***	0.706	44.4***
Panel B. Pre-crisis period, 2006/12/1–2008/9/14									
N	465	465	465	465	465	465	465	465	465
Mean	0.134	0.119	0.095	0.199	0.133	0.084	0.403	0.037	0.393
S.D.	0.072	0.067	0.096	0.066	0.068	0.061	0.052	0.055	0.06
Skewness	0.708	-0.484	0.544	0.030	0.174	0.247	0.078	0.025	0.181
Kurtosis	0.228	0.577	-0.176	-0.35	-0.466	0.60	-1.012	0.017	-0.776
JB test	39.98***	24.627***	23.557***	2.447	6.549**	11.759***	20.374***	0.054	14.24***
Panel C. The first phase of the crisis period, 2008/9/15–2009/9/14									
N	260	260	260	260	260	260	260	260	261
Mean	0.231	0.266	0.170	0.309	0.178	0.148	0.447	0.056	0.461
S.D.	0.068	0.067	0.075	0.053	0.066	0.087	0.033	0.050	0.039
Skewness	-0.129	-0.495	0.206	-0.011	-0.206	-0.261	0.567	-0.421	-0.012
Kurtosis	-0.181	-0.534	-0.792	0.037	-0.871	-0.016	-0.246	0.318	-0.589
JB test	1.083	13.795***	8.682**	0.020	10.104***	2.966	14.681***	8.790**	3.781
Panel D The second phase of the crisis period, 2009/9/15–2011/12/30									
N	599	599	599	599	599	599	599	599	599

Mean	0.226	0.168	0.123	0.283	0.167	0.167	0.416	0.048	0.421
S.D.	0.068	0.068	0.056	0.060	0.058	0.071	0.051	0.069	0.054
Skewness	-0.398	0.133	-0.360	-0.518	0.068	-0.266	0.185	0.182	0.16
Kurtosis	0.020	0.594	-0.179	-0.432	-0.396	-0.634	-0.754	-0.380	-0.622
JB test	15.78***	10.58***	13.747***	31.435***	4.392	17.11***	17.633***	6.911**	12.217***
Panel E Post-crisis period, 2012/1/1-2014/2/28									
N	565	565	565	565	565	565	565	565	565
Mean	0.189	0.175	0.063	0.244	0.131	0.103	0.372	0.063	0.36
S.D.	0.072	0.071	0.064	0.078	0.093	0.075	0.061	0.053	0.067
Skewness	-0.164	-0.205	-0.187	-0.384	-0.103	0.053	-0.187	-0.301	-0.063
Kurtosis	-0.626	-0.289	-0.032	-0.723	-0.624	-0.627	-1.265	0.365	-1.246
JB test	11.779***	5.92*	3.322	26.17***	10.176***	9.51***	40.973***	11.692***	36.907***

Notes: *N* is the sample size and S.D. stands for standard deviation. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. JB test corresponds to the Jarque–Bera test statistics.

Table 1.6. Estimations of the DCCX and DECOX models

	DCCX								DECOX
	United States–Hong Kong	United States–Thailand	United States–Malaysia	United States–Singapore	United States–Indonesia	United States–Taiwan	United States–Korea	United States–Philippine	Nine sample markets
γ_0	-1.977***	-2.329***	-2.010***	-1.492***	-2.154***	-2.730***	-1.789***	-3.002***	-1.094***
	(0.041)	(0.062)	(0.091)	(0.035)	(0.043)	(0.724)	(0.034)	(0.171)	(0.008)
γ_1	-	-	-	-	-	0.000**	-	0.000***	-
						(0.000)		(0.000)	
γ_2	-0.003***	-0.003***	-0.004***	-0.003***	-0.001***	-0.002***	0.002***	-0.003***	-
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
γ_3	0.010***	0.013***	0.002	0.005***	0.011***	0.004	-0.006***	0.029***	0.007***
	(0.002)	(0.004)	(0.005)	(0.001)	(0.004)	(0.006)	(0.002)	(0.007)	(0.000)
γ_4	-0.070***	0.063**	-0.187***	-0.033***	-0.010	-0.044***	-0.028	0.094**	0.0002**
	(0.0000)	(0.031)	(0.045)	(0.011)	(0.008)	(0.140)	(0.027)	(0.038)	(0.000)
DM_1	0.525***	0.975***	0.558***	0.414***	0.252***	0.091	-0.129**	0.239	-0.071
	(0.075)	(0.089)	(0.174)	(0.056)	(0.068)	(0.078)	(0.064)	(0.179)	(0.015)
DM_2	4.410***	0.388***	-0.108	0.187***	0.034	0.400	0.115*	0.205	0.041***
	(0.055)	(0.090)	(0.178)	(0.048)	(0.058)	(0.045)	(0.065)	(0.151)	(0.008)
Log-likelihood	-538.375	-805.065	-1086.214	-68.073	-694.898	-621.766	-339.067	-933.966	1197.759

Notes: The numbers in parentheses are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. x_0 is a constant, x_1 is foreign investment, x_2 is the sovereign CDS premium, x_3 is the VIX index and x_4 is the TED spread. "-" denotes that there are insufficient observations.

Table 1.7. Statistical loss functions (MSE $\times 10^{-3}$) of the DCC- and DCCX-MGARCH models

Window	United States–Hong Kong		United States–Thailand		United States–Malaysia		United States–Singapore	
	DCC	DCCX	DCC	DCCX	DCC	DCCX	DCC	DCCX
250	6.265	4.652	6.901	6.128	6.717	4.031	6.973	6.541
300	6.205	4.334	7.734	6.782	5.795	3.801	6.427	6.738
350	6.198	4.147	8.412	7.477	5.982	3.522	7.184	7.006
400	6.625	4.126	9.186	8.256	6.286	3.052	7.975	7.196
Window	United States–Indonesia		United States–Taiwan		United States–Korea		United States–Philippine	
	DCC	DCCX	DCC	DCCX	DCC	DCCX	DCC	DCCX
250	5.983	5.821	13.437	13.300	10.454	7.973	6.525	5.886
300	5.58	5.381	13.527	13.379	8.944	6.839	6.644	4.474
350	5.676	5.249	13.777	13.367	8.082	5.649	6.505	3.627
400	6.151	5.284	13.689	13.522	7.091	4.642	5.966	3.194

Table 1.8. Statistical loss functions (MSE $\times 10^{-2}$) of the DECO- and DECOX-MGARCH models

Window	DECO	DECOX
250	5.982	5.872
300	5.708	5.707
350	5.511	5.502
400	5.478	5.427

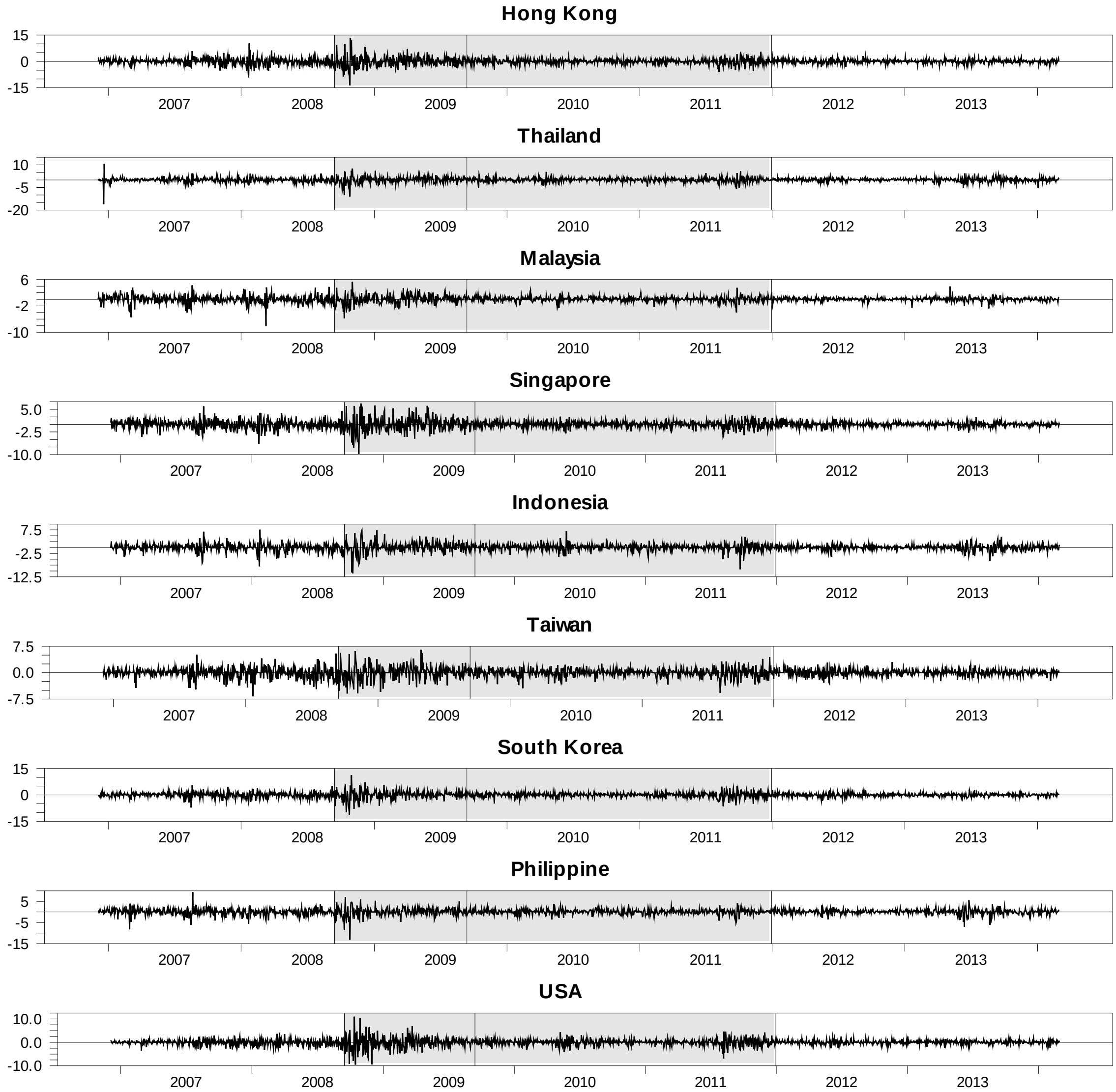


Fig. 1.1. Daily stock returns of the eight East Asian countries and the US

Note: The shaded area illustrates the periods of the first and second phases of the global financial crisis.

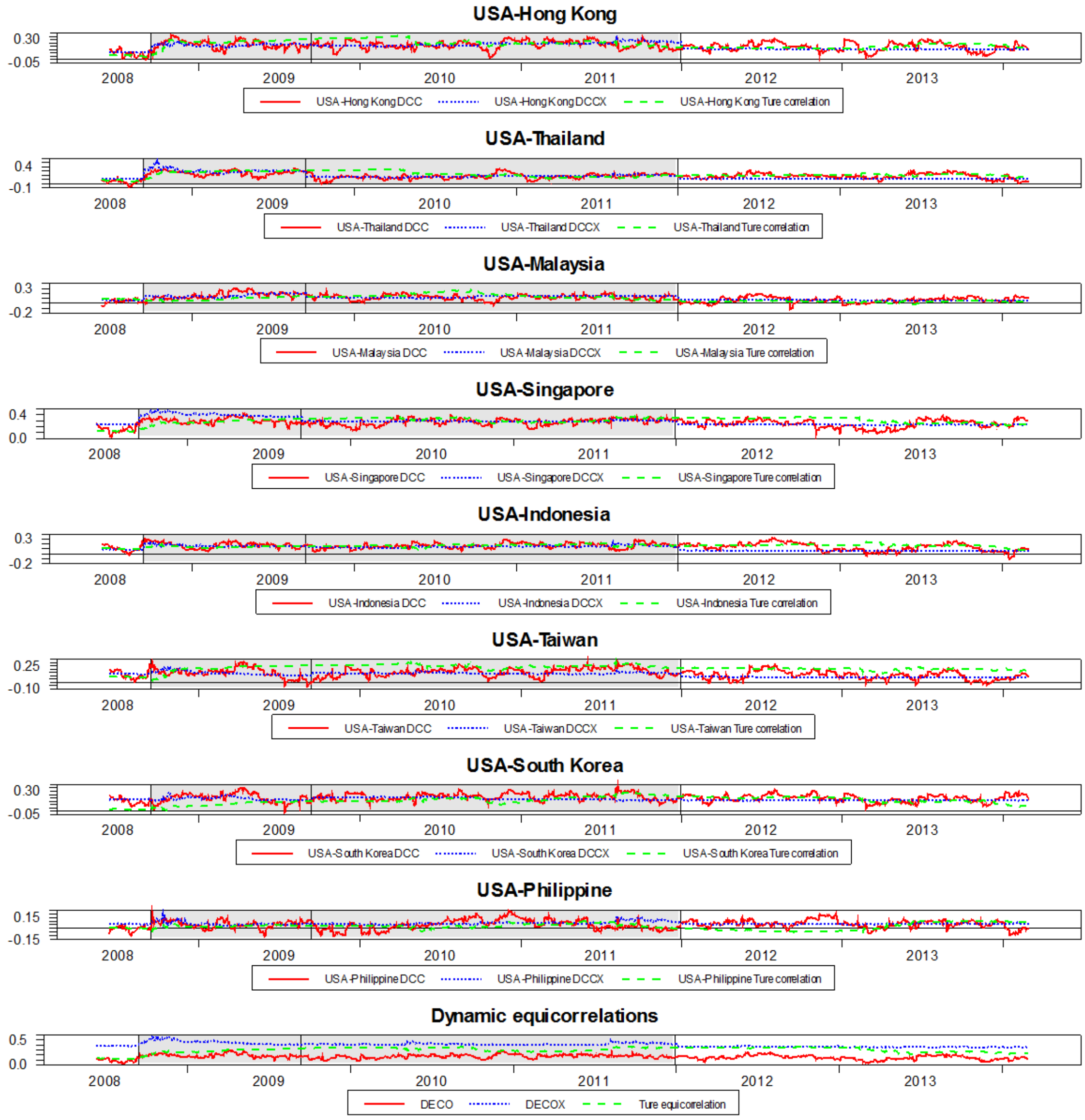


Fig. 1.2. Dynamic conditional correlations and equicorrelation estimated by DCC- and DECO-MGARCH model, DCCX and DECOX model, and the true correlations and equicorrelation approximatedy by 400-day rolling window correlations and equicorelation.

Note: The shaded area illustrates the periods of the first and second phase of the global financial crisis.

Chapter 2

Interdependence between oil and East Asian stock markets: Evidence from wavelet coherence analysis

2.1 Introduction

Crude oil is pertinent for the real economy and financial markets worldwide. Particularly, few economies in the world rely on oil imports to the same extent as East Asia. East Asia includes three of the world's top ten oil-importing nations –China (China represents Chinese mainland in our paper), Japan, and South Korea. Each of these three nations, as well as other nations in East Asia, shows an increasing demand for oil. Many studies focus on the developed countries while few studies analyze the interdependence between oil and East Asian markets. In fact, this is an important and interesting subject because the East Asian region, which is experiencing rapid economic growth, is the region most likely to increase its demand for oil and become a larger player in the global financial markets. Moreover, the majority of East Asian oil imports are from the volatile Middle East, and there has been no regional mechanism in East Asia to stockpile emergency petroleum supplies (Shin and Savage, 2011), which makes East Asia highly susceptible to oil shocks such as the 2003 Iraq invasion or the 2006 OPEC cut agreement.

In our paper, we investigate the interdependence between oil price and East Asian stock markets, since an understanding of volatility and correlation are essential for derivative pricing, portfolio optimization, risk management, and hedging for East Asian financial markets. Despite there is the rather scarce literature, some authors state that there is a weak or negative link for the sample East Asian countries (Basher and Sadorsky, 2006; Zhu et al., 2014). These results are consistent with economic theory because rising oil prices increase production cost, have an adverse effect on cash flows, and reduce stock prices.[2] The study results conclude that oil is an effective diversification tool for East Asian stock markets. This feature is also reflected in international investors' preference to diversify risk. However, the limitation of the previous empirical studies is that they are restricted to one or, at most, two time scales – the short and long term. In fact, international investors should be heterogeneous with respect to their different investment horizons.

We offer two contributions in this paper. First, we employ the wavelet coherence analysis to analyze oil-stock interdependence. Wavelet analysis offers a huge advantage in that it provides a framework to measure the frequency components of dynamic movement without losing time-specific information. Additionally, we employ the recently developed wavelet coherence analysis (Grinsted et al., 2004), which exposes regions in terms of the degree and direction (in phase or out phase) of co-movement and simultaneously reveals the effect-result relationship in time-frequency space. Second, we measure the oil-stock portfolio diversification benefits that are implied by our model using the appealing framework of Reboredo and Rivera-Castro (2014b). We assess the risk reduction by calculating the ratio between the oil-stock mixed portfolio variance and the stock variance in the time-frequency domain and measuring the Value at Risk (VaR) and Expected Shortfall (ES) in the oil-stock portfolios.

The remainder of this article is organized as follows. Section 2 is devoted to explaining the methodology, Section 3 describes data. Section 4 presents the empirical results. Finally, Section 5 concludes.

[2] Stock prices can be explained using an equity pricing model in which the price of equity at any point in time is equal to the expected discounted cash flows.

2.2 Methodology

2.2.1 Wavelet

Wavelet functions are constructed based on location, scale parameters, and a mother wavelet function, $\psi \in L^2(\mathbb{R})$, defined as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), s, \tau \in \mathbb{R}, s \neq 0 \quad (2.1)$$

where the term $\frac{1}{\sqrt{|s|}}$ denotes a normalization factor ensuring unit variance of the wavelet and $\|\psi_{\tau,s}\|^2 = 1$. s is a scaling factor that controls the width of the wavelet. Scale has an inverse relation to frequency. Accordingly, a higher scale suggests a stretched wavelet that is appropriate for detection of a lower frequency. τ is a translation parameter that controls the location of the wavelet.

There are many types of wavelets with different specifications that are used for different purposes[3]. We use the Morlet wavelet that was first introduced by Goupillaud, et al. (1984). Formally, the Morlet wavelet is defined as:

$$\psi^M(t) = \frac{1}{\pi^{1/4}}e^{i\omega_0 t}e^{-t^2/2} \quad (2.2)$$

where $\frac{1}{\pi^{1/4}}$ ensures unity energy of the wavelet. ω_0 is the dimensionless frequency and denotes the central frequency of the wavelet. ω_0 usually equals six in practice because this value can ensure that the Fourier frequency period (*1/f*) is almost equal to

[3] For more details, see Percival and Walden (2000); Addison (2002).

scale (s)[4]. $\omega_0 = 6$ is a good choice that satisfies the admissibility condition[5] (Farge, 1992) and enables a balance between time and frequency localizations (Grinsted et al., 2004; Rua and Nunes, 2009) often used in economic applications (Vacha and Barunik, 2012; Yang and Hamori, 2015; Aloui et al., 2016). As noted by Addison (2002), the Morlet wavelet is a complex or analytic wavelet within a Gaussian envelop with good time-frequency localization.

2.2.2 Continuous wavelets

Given a time series $y(t) \in L^2(\mathbb{R})$, its continuous wavelets (CWT) with respect to the wavelet ψ is a function of two variables, $W_{y;\psi}(\tau, s)$:

$$W_{y;\psi}(\tau, s) = \int_{-\infty}^{\infty} y(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t-\tau}{s}\right) dt \tag{2.3}$$

where * denotes the complex conjugate form. The wavelet transform can give us information simultaneously on time-frequency space by mapping the original time series into the function of τ and s. Additionally, because both τ and s are real values and vary continuously, $W_{y;\psi}(\tau, s)$ is named a continuous wavelet transform (Jiang et al., 2015).

By inversing the CWT, we can reconstruct a time series $y(t) \in L^2(\mathbb{R})$ using the formula

[4] For the particular choice of $\omega_0 = 6$, we can simply use the approximate equation that $f = \frac{\omega_0}{2\pi s} = \frac{6}{2\pi s} \approx 1/s$ implying that broad-scale s corresponds to low Fourier frequency f while fine-scale s corresponds to high Fourier frequency f.

5 The admissibility condition is defined as $0 < C_\psi = \int_0^\infty \frac{|\Psi(f)|^2}{f} df < \infty$. See Daubechies (1992) for more details.

$$y(t) = \frac{1}{C_\psi} \int_0^\infty [\int_{-\infty}^{\infty} W_{y;\psi}(\tau, s)\, \psi_{\tau,s}(t) d\tau] \frac{ds}{s^2}, \quad s > 0 \tag{2.4}$$

Moreover, the energy of the examined time series is preserved by its CWT in the sense that

$$\|y\|^2 = \frac{1}{C_\psi} \int_0^\infty [\int_{-\infty}^{\infty} |W_{y;\psi}(\tau, s)|^2 \, d\tau] \frac{ds}{s^2}, \quad s > 0 \tag{2.5}$$

where $|W_{y;\psi}(\tau, s)|^2$ is defined as a wavelet power spectrum (WPS) that can interpret the degree of local variance of $y(t)$ scale by scale. Formally, the function of WPS is as follows:

$$(WPS)_y(\tau, s) = |W_y(\tau, s)|^2 \tag{2.6}$$

According to Grinsted et al. (2004), the statistical significance can be assessed against the null hypothesis that the time series generating process is given by an AR(1) stationary process with a certain background power spectrum (P_f)[6]. Torrence and Compo (1998) compute the white noise and red noise wavelet power spectra based on Monte Carlo simulations and derive that the corresponding distribution for the local wavelet power spectrum under the null hypothesis are as follows

$$D\left(\frac{|W_{y,t}(s)|^2}{\sigma_y^2} < p\right) = \frac{1}{2} P_f \chi_v^2 \tag{2.7}$$

at each time *t* and scale *s*. P_f is the mean spectrum at the Fourier frequency *f* that corresponds to the wavelet scale *s* ($f \approx 1/s$). *v* is equal to one or two for real or complex wavelets, respectively. Therefore, in our analysis, oil price or stock returns with high

6 The Fourier power spectrum of an AR(1) process with lag-1 autocorrelation α is given by $P_f = \frac{1-\alpha^2}{|1-\alpha e^{-2i\pi k}|^2}$ (estimated from the observed time series, e.g., Allen and Smith, 1996)

power spectrum in time-frequency space suggests that the degree of local variance is high.

2.2.3 Cross-wavelet power, wavelet coherence, and phase differences

WPS assesses the local variance degree of a single signal while detecting and quantifying relationships between two time series are necessary in many applications. The cross-wavelet transform, wavelet coherency, and wavelet phase-difference are the basic wavelet analysis tools that can manage time-frequency dependencies between two time series.

Given two time series, *x(t)* and *y(t)*, with wavelet transforms, W_x and W_y, first introduced by Hudgins et al. (1993) are simply defined as $W_{xy} = W_x W_y^*$ where W_y^* is the complex conjugate of W_y. The cross-wavelet power (XWP) is

$$(XWP)_{xy} = |W_{xy}| \tag{2.8}$$

The XWP of two time series depicts the local covariance between them at each time and frequency and shows the area in the time-frequency space where the two signals exhibit high common power. Therefore, the XWP gives us a quantified indication of the similarity of power between two time series. Torrence and Compo (1998) also derive the theoretical distribution of the XWP of two time series with background power spectra P_f^x and P_f^y, as follows

$$D\left(\frac{|W_{x,t}(s)W_{y,t}^{*}(s)|}{\sigma_x\sigma_y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_f^x P_f^y} \tag{2.9}$$

where $Z_v(p)$ is the confidence level associated with the probability p for a pdf defined by the square root of the product of two χ^2 distributions[7]. In our analysis, we use XWP to investigate the degree of the local covariance of East Asian oil and stock returns.

Another useful measure assessing the relationship between two time series is the coherency of the cross wavelet in time-frequency space. As Torrence and Compo (1998) and Aguiar-Conraria et al. (2008) explain, wavelet coherency can be defined as the ratio of the cross spectrum to the product of each series spectrum and can be thought of as the local correlation between two time series in time-frequency space. Following Torrence and Webster (1999), wavelet coherency (WTC) can be defined by

$$R_{xy}{}^2 = \frac{|S(W_{xy})|^2}{S(|W_x|^2)\,S(|W_y|^2)} \tag{2.10}$$

where S is a smoothing operator in both time and scale. Without smoothing, coherency is identically one at all scales and times (see Grinsted et al. (2004) and Cazelles et al. (2007) for details.). After smoothing, the squared WTC gives a quantity between zero and one in a time-frequency space, $0 \le R_{xy}{}^2 \le 1$. Obviously, $R_{xy}{}^2$ close to zero indicates a weak correlation while $R_{xy}{}^2$ close to one provides evidence of strong correlation. Because the theoretical distribution for the WTC is not derived, we estimate the statistical significance level of the WTC based on Monte Carlo methods (Grinsted et al. 2004). In our analysis, this estimation helps us to investigate the degree of interdependence between East Asian oil and stock return by calculating the local correlation.

Because of the squared WTC, we cannot distinguish between positive and negative

[7] For example, in our analysis, the 5% significance level is calculated using $Z_2(0.95) = 3.999$.

correlations. We require the phase difference tool to present positive or negative correlations and lead-lag relationships between two time series as a function of frequency. Because the CWT is complex, it can be divided into a real part and an imaginary part. Following Bloomfield et al. (2004), WTC phase difference can be defined by

$$\phi_{xy} = \arctan\left(\frac{\Im\{s(s^{-1}W_{xy})\}}{\Re\{s(s^{-1}W_{xy})\}}\right), with\ \phi_{xy} \in [-\pi, \pi] \tag{2.11}$$

where $\Im$ and $\Re$ are the imaginary and real parts of the smoothed XWT, respectively. A phase-difference of zero indicates that the time series move together at the specified time-frequency. If $\Phi_{xy} \in \left(0, \frac{\pi}{2}\right)$, then the series move in phase, but the time series x leads y; if $\Phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$, then it is y that is leading. A phase-difference of π or $-\pi$ indicates an anti-phase relation; if $\Phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, then y is leading; time series x is leading if $\Phi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right)$.

Additionally, following Aguiar-Conraria, et al. (2012), Aguiar-Conraria and Soares (2013) and Jiang et al. (2015), we can easily convert the phase difference into the instantaneous time lag between x(t) and y(t) in the sense that

$$(\Delta t)_{xy} = \frac{\phi_{xy}}{\omega(s)} \tag{2.12}$$

where $\omega(s)$ is the angular frequency corresponding to the scale s in the sense that $\omega(s) = 2\pi f$. We have the Fourier frequency $f \approx 1/s$ with the particular choice of $\omega_0 = 6$. Thus, $\omega(s) = 2\pi/s$, and the instantaneous time lag is given by

$$(\Delta t)_{xy} = \frac{\phi_{xy} \cdot s}{2\pi} \tag{2.13}$$

In our analysis, we interpret the phase difference in terms of the arrow directions in the WTC plots. Arrows pointed to the right (or left) imply that two time series are in phase (or out of phase). Arrows pointing up and down imply a causality relationship between them. Specifically, if arrows point straight up (down), the first variable x(t) is leading (lagging).

2.3 Data

The primary crude oil benchmark prices in the world include Brent Crude, the Organization of Petroleum Exporting Countries (OPEC) Reference Basket (ORB), and West Texas Intermediate (WTI). Brent Crude is a generally accepted world benchmark price, although the sales volumes of Brent Crude itself are far below other benchmarks. ORB is a weighted average of prices for petroleum blends produced by OPEC countries. WTI oil prices is the most widely used oil price index in the world published by the United States Energy Information Administration. Our data are composed of daily WTI spot oil prices representing the oil price series given its relevance to the countries in our sample.

For East Asian stock markets, we choose 10 East Asian countries or regions of the Asia-Pacific Economic Cooperation (APEC) – China (Shanghai Stock Exchange A shares), Chinese Taipei (Taiwan Stock Exchange Weighted Index), Hong Kong (Hang Seng Index), Indonesia (MSCI Indonesia), Japan (Topix), Malaysia (MSCI Malaysia), the Philippines (Philippine Stock Exchange Index), Singapore (MSCI Singapore), South Korea (Korea Stock Exchange Composite Index), and Thailand (Bangkok Stock Exchange Index). The logarithmic difference of the transformed data is used for further analysis. The use of daily data is appropriate to capture the rapidity and intensity of the dynamic interdependence between oil and stock markets (Madaleno and Pinho, 2014). As Reboredo and River-Castro (2014a) and Gallegati (2012) show, given that shock impacts are fast and dwindle after a few days, correlation vanishes in a matter of days. Therefore, an analysis using daily data can provide more insightful empirical results than weekly or monthly data. We investigated the dynamic interdependence between oil and East Asian stock returns from January 3, 1992 to October 22, 2015 with a total number of 6210 observations. All data sets were obtained from Datastream.

Table 2.1 gives the descriptive statistics of the asset returns. We find positive average WTI oil and stock returns for all East Asian stock markets except Japan, and the obtained means are very close to zero. We realize that the oil index and China stock market exhibit greater variability than the other returns and we emphasize that Chinese stock returns display the highest volatility level among East Asian stock markets. All return distributions seem against normal as measured by the skewness and kurtosis statistics. Additionally, the Jarque-Bera test statistics are highly significant confirming the non-normal distribution. More precisely, all the daily returns exhibit asymmetry and show positive or negative skewness, and all return distributions perform excess kurtosis.

Insert Table 2.1 here

Table 2.2 shows the pairwise return correlations for all pairs of indexes in our sample. We find a weak positive relationship between oil and East Asian stock markets with maximum values of 0.0917 for Hong Kong markets followed by Indonesia, Singapore, and Japan. Zhu et al. (2014) show that weak correlations may be attributed to rapid growth in the East Asian economy during the sample periods. We expect that these will be the stock markets that show greater co-movement with the WTI oil index in the wavelet coherency plots. Chinese stock returns exhibit the lowest correlation (0.0228) with oil price given that the domestic oil price in China fluctuates less than the world oil price because it is controlled by the Chinese government. Therefore, world oil shocks do not significantly affect the Chinese economy. The Chinese stock returns also show the lowest correlation with the remaining East Asian countries ranging between 0.1541 (with Hong Kong) and 0.0499 (with Malaysia).

Insert Table 2.2 here

In Fig.2.1, we graph the time series plots of oil and East Asian stock prices and returns in the top and middle parts of each plot. Several historical events are identified below the plots by alphabet, which may provide some correlation with the behavior presented by the series. From the top and middle parts of each plot in Fig. 2.1, we find that oil prices were relatively stable in the long term from 1992 to 2006 and considerably increased from 2006 to 2008 covering the periods of OPEC cuts and the global financial crisis. The oil returns also show high volatility during the global financial crisis. We find that all stock indexes have decreased since the global financial collapse. The returns of the 10 East Asian stock indexes also show high volatility during the crisis period.

Insert Figure 2.1 here

2.4 Empirical results

In this section, we first graph the wavelet power spectrum plots of oil and stock returns illustrating the localized volatility of series in time-frequency space. Second, we employ the cross wavelet power, wavelet coherence analysis, and phase difference to investigate the covariance, the degree of the interdependence, and the lead-lag effect relationship between oil and stock returns. Finally, we compute the ratio of portfolio variance to provide some financial insights to the wavelet coherence analysis for portfolio allocation and risk management for East Asian markets.

2.4.1 Wavelet analysis

In our paper, we decompose the data series up to 12 levels[8], covering the short-term horizon (less than one year), the midterm horizon (from one year to eight years), and the long-term horizon (from eight years to 16 years).

The bottom parts of each plot in Fig. 2.1 illustrate the continuous wavelet power spectrum for the WTI oil prices and for the 10 selected East Asian stock returns. In the wavelet power spectrum, the black contour shows the 5% significance level estimated from Monte Carlo simulations, the color code for power ranges from blue (low power) to red (high power), and the bold line shows the cone of influence indicating the region affected by edge effects[9]. Several historical episodes are identified below the plots by alphabets. According to the wavelet power spectrum plots in Fig. 2.1, we find that most actions in the indexes occurred at high scales (low frequencies). From 2007 to 2009, during the sub-prime crisis, the global financial collapse, and the European sovereign debt crisis we see a dark contour in the 256 to 512-day scales for the oil index returns,

[8] The various decomposition levels we obtain correspond to time scales: level 1 (one to two days); level 2 (two to four days); level 3 (four to eight days); level 4 (eight to 16 days); level 5 (16 to 32 days); level 6 (32 to 64 days); level 7 (64 to 128 days (half a year)); level 8 (128 to 256 days (one year)); level 9 (256 to 512 days (two years)); level 10 (512 to 1,024 days (four years)); level 11 (1,024 to 2,048 days (eight years)); level 12 (2,048 to 4,096 days (16 years)).

[9] See Grinsted et al. (2004) for more details.

implying more volatile in the medium horizon for the oil series. For the stock returns, we find that the volatilities of China and Japan stock index returns were stronger in the 512 to 1,024 and 1,024 to 2,048-day scales from 2005 to 2008 covering the London bombings, the OPEC cut agreement, the sub-prime financial crisis, and the global financial crisis periods. Hong Kong, Indonesia, Malaysia, the Philippines, Singapore, Taiwan, and Thailand stock indexes show high variation in all the day scales from the year 1997 to the year 2000 and in the 256 to 512-day scale from 2007 to 2009. This result suggests that the variances of these East Asian stock returns are higher in all time horizons during the Asian financial crisis, the Russian financial crisis, the 1999 OPEC cut agreement, and the Internet bubble while there is high power in the medium-run scale for the global financial crisis period. This high power is consistent with Jammazi (2012), who finds that variances at intermediate scales are transition periods between turbulent and persistent fluctuation periods. The same happens for all the day scales for the South Korea stock index between the mentioned historical episodes from the year 1997 to the year 2000 while the difference is that more power exists at high frequencies during the global financial crisis period.

Fig. 2.1 shows the local variance degree of a single time series. Investigating the interdependence between two series is of greater significance to our paper; thus, we plot the cross-wavelet transform that can exhibit high common power between the oil-stock pairs in Fig. 2.2. Similar to the wavelet power spectrum plots in Fig. 2.1, the black contour shows the 5% significance level, and the color code reflects the strength of covariance ranging from blue (low power) to red (high power). Fig. 2.2 also provides the relative phasing of two series using phase arrows, which indicates the direction of interdependence and cause–effect relationships. If the arrow points right, the pair is in phase where arrows point to the right and up (the phase difference $\Phi_{xy} \in \left(0, \frac{\pi}{2}\right)$) with the former variable leading, and arrows point to the right and down (the phase difference $\Phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$) with the former lagging. If the arrow points left, it is anti-phase if arrows point to the left and up (the phase difference $\phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$) with the former lagging while arrows point to the left and down (the phase difference $\phi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right)$) with the former leading.

Insert Figure 2.2 here

Fig. 2.1 reveals that most high variance is at lower frequency and verifies the same in terms of covariance as Fig. 2.2. Fig. 2.2 shows a dark contour in the 512 to 1,024- day scales from 2006 to 2009 for the oil-China pairs, implying that significant high common power between oil and Chinese stock market occurred in the midterm run scale during the episodes of the OPEC cut agreement, the sub-prime crisis, the global financial turmoil and, finally, the European sovereign debt crisis. For the pairs between oil and the remaining nine East Asian stock markets, most high covariance between them occurs in the 512 to 1,024-day scales or the 256 to 512-day scales during the two financial crisis periods of 1997 to 2001 and 2007 to 2009. Fig. 2.2 leads to some conclusions on phase information. The arrows pointing right and left and down and up, constantly, imply that the interdependence between oil and different stock markets was not homogeneous across different time and scales. For example, in the 512 to 1,024-day bands and associated with the global financial collapse in 2008 and the European sovereign debt crisis in 2009 for the oil-China plot, the arrows point right and up, implying that oil and Chinese stock indexes are in phase and the oil price led that crisis period. For the pairs of the oil-Japan plot, arrows point right both in the 512 to 1,024 day-bands from 1997 to 2000 and in the 256 to 512-day bands from 2007 to 2009, which implies that oil and Topix indexes are in phase. The same occurs for the interdependence between oil and the remaining East Asian stock markets; arrows point right and up implying the lead of oil prices.

We also plot the wavelet coherence and phase of the oil index and East Asian stock index in Fig. 2.3 to investigate the degree of correlation and the lead-lag relationship between them. As in Figs.2.1 and 2.2, Monte Carlo simulations are used to assess the statistical significance of the local correlation in the time-frequency domain. Color coding varying from blue to red indicates the values of coherence from zero to one. Thus, regions inside the black contour plotted in warmer colors represent regions with significant strong interdependence. The arrows pointing right and left and up and down imply the direction of interdependence and causality between oil and stock, as in Fig. 2.2. Fig. 2.3 shows that the most significant higher correlation between oil and all stock markets occurs at lower frequencies, which is consistent with the results of Fig. 2.2. Particularly, there are many statistically significant regions both in the midterm and the long term for almost all sample periods in the stock markets such as Hong Kong, Indonesia, Korea, Malaysia, Singapore, and Thailand, which are more pronounced than the other East Asian countries. The result is consistent with the Pearson correlation in Table 2.2. The exceptions are for the Chinese stock market where significant regions of coherence occurred in the 256 to 512-day scales from 2005 to 2009 and the Japanese stock market where we were expecting higher coherence in Table 2.2. Our results suggest no strong interdependences between oil prices and Chinese stock returns and between oil prices and Japanese stock returns. The weak correlations between oil prices and stock returns are attributed to high capitalization in China and a strong Japanese economy that was relatively invulnerable to changes in oil prices. In the significant regions, phase arrows point right and up implying that both variables are in phase with oil prices leading. However, oil prices were lagging stock returns in the 128 to 256-day scales during the 1997 Asian financial crisis and the global financial crisis, confirming the findings of Madaleno and Pinho (2014).

Insert Figure 2.3 here

Fig. 2.4 provides a more detailed analysis of wavelet coherence of oil-stock pairs and phase difference from level 8 to level 12 covering the midterm and the long horizon. The left vertical axis (blue line) is for coherence. If the value of coherences is close to one, this implies a high interdependence between two time series, and those near zero show no relationship. The right vertical axis (green line) is for phase difference varying from $-\pi$ to π. Fig. 2.4 shows that coherencies are more stable in the higher scales (lower frequencies) or the long run while they show relatively high volatility in the high frequencies. We also realize that the values of coherences in the 512 to 1,024 and 256 to 512-day scales are the highest, implying that oil prices are most strongly related to East Asian stock returns in the midterm. Moreover, we find that there are more pronounced increases in the higher frequencies during the Asian financial crisis in 1997 and the global financial collapse in 2008. Phase difference is the same as coherence and is more erratic at higher frequencies. For most scale bands, we find the values of phase difference varying from $-\pi/2$ to $\pi/2$, implying that oil prices and stock returns have a positive relationship during the sample periods. We infer that in the highest scale of the 2,048 to 4,096-day band, the phase difference reaches between zero and $\pi/2$ suggesting that oil prices lead to East Asian stock returns in the long-term horizon. Additionally, we find that the value of phase drops to minus during the Asian financial crisis in 1997 and the global financial collapse in 2008, implying that oil prices were lagging stock returns during crisis periods, which is consistent with Fig. 2.3 and confirms the findings of Madaleno and Pinho (2014). The relationship between oil and stock are consistent with economic theory because the changes in oil prices have an effect on production cost and, thus, affect the change of cash flows and stock prices during the turmoil period. Additionally, East Asian stock markets have contagion effect during the turmoil from the US stock markets, which affects oil prices. Hence, oil prices were lagging stock returns during the crisis period.

Insert Figure 2.4 here

Considering the sub-periods in the spirit of Naccache (2011), we similarly present the average value of coherence and phase difference of oil for the selected 10 East Asian stock markets for five sub-periods in Table 2.3 and 2.4. From Tables 2.3 and 2.4, we observe that the maximum values of coherence between oil and stock are above 0.6 in the 256 to 512, 512 to 1,024, and 1,024 to 2,048- day bands (midterm run) during all periods except for China (0.5251) and Japan (0.5270), which is consistent with the wavelet coherence plots of Fig. 2.3. Considering the five sub-periods, the average coherency values are relatively higher between the year 1997 to 2001 and the year 2007 to 2011 covering two regional and global financial crises – the Asian financial crisis and the global financial collapse. Comparing the two crises, there are two commonalities. The first is that all the maximum average values are located in the midterm horizons. The second is that the values hardly change in the long-term run of the eight to 16 year-band. We then argue the different parts of the two crises. The coherency values of the global financial crisis are higher than the values of the Asian financial crisis. The global financial crisis hardly affected the average values in the short-term horizon of less than one one year while the values obviously increased during the Asian financial crisis consistent with the findings of Madaleno and Pinho (2014) who suggest that coherencies are higher during crisis periods and at higher scales. The result implies that oil and East Asian stock markets experienced contagion effect during the global financial crisis period[10]. With respect to the phase difference values, we find that the mean phase difference values almost range from $-\pi/2$ to $\pi/2$ during all the sub-periods, implying a positive relationship between oil and East Asian stock markets. Additionally, the mean values of all sub-periods in the 2,048 to 4,096-day band belong to $(0, \pi/2)$ suggesting that oil and stock move in phase and that oil prices lead to stock returns in the long-run cycle. In the medium and short-term scales, the phase difference negative and positive values change across scales within periods.

Insert Table 2.3 and 2.4 here

2.4.2 Risk management

In this section, we evaluated whether oil is useful to diversify the East Asian stock portfolios by assessing the risk reduction. Specifically, we first calculated the ratio between the oil-stock mixed portfolio variance and the stock variance in the

[10] Gallegati (2012) proposes wavelets to identify contagion (changes in higher frequencies) and interdependence (lower frequencies) among oil and stock markets.

time-frequency domain. We also measured the downside risk reduction by two ways-Value at Risk (VaR) and Expected Shortfall (ES) in the oil-stock portfolios with respect to the stock portfolio. In our paper, we consider an optimal weighted oil-stock portfolio and according to Kroner and Ng (1998), the weight of oil in the oil-stock portfolio is defined as:

$$w_{s,t}^{oil} = \frac{\sigma_{s,t}^{2\ stock} - cov(r^{oil}, r^{stock})_{s,t}}{\sigma_{s,t}^{2\ oil} - 2cov(r^{oil}, r^{stock})_{s,t} + \sigma_{s,t}^{2\ stock}} \tag{2.14}$$

where s is the time scales and $w_{s,t}^{oil} = 0$ when $w_{s,t}^{oil} < 0$, $w_{s,t}^{oil} = 1$ when $w_{s,t}^{oil} > 1$.

$w_{s,t}^{stock} = 1 - w_{s,t}^{oil}$. We compute the time-scale variance and covariance using the wavelet coherence counterparts of variance and co-variance in Eq. (10). Thus, the portfolio mean and variance is given by:

$$r_{s,t}^{portfolio} = w_{s,t}^{oil} r_t^{oil} + w_{s,t}^{stock} r_t^{stock} \tag{2.15}$$

$$\sigma_{s,t}^{2\ portfolio} = w_{s,t}^{oil} \sigma_{s,t}^{2\ oil} + w_{s,t}^{stock} \sigma_{s,t}^{2\ stock} + w_{s,t}^{oil} w_{s,t}^{stock} cov(r^{oil}, r^{stock})_{s,t} \tag{2.16}$$

Following Reboredo and Rivera-Castro (2014b), the risk reduction is defined as the percentage reduction in the oil-stock portfolio variance with respect to the stock portfolio:

$$RR_{s,t} = 1 - \frac{\sigma_{s,t}^{2\ portfolio}}{\sigma_{s,t}^{2\ stock}} \tag{2.17}$$

A higher value of $RR_{s,t}$ means greater oil-stock optimal weight portfolio reduced risk better, Moreover, values of $RR_{s,t}$ varying over time and different scales implies an evolving risk reduction at different horizons. That is convenient for the international short and long-term investors who are more interested on short and long-run risk reduction. Fig.2.5 shows the plots of the risk reduction of the oil-stock optimal weight portfolio for East Asian countries respectively. Fig.2.5 shows the value is always bigger than zero for all countries and for all frequencies in time, implying that oil is useful in reducing risk for portfolios in all time-frequency spaces. Moreover, the value is different across frequencies and times. For example, risk reduction increase with the time scales in the oil-Chinese stock portfolio. Specifically, over the Asian financial crisis period, oil did a good job as a diversifier in the 512-1024 time scales. The results suggest the importance of correctly selecting the investment horizon.

Insert Figure 2.5 here

We also measure the downside risk reduction (DRR) by calculate the ratio between the oil-stock portfolio VaR and ES with respect to those of the stock portfolio respectively.

The VaR at the $(1-\alpha)\%$ confidence level of a portfolio is defined as:

$$VaR_{s,t} = V_0 \emptyset^{-1}(1-\alpha)\sigma_{s,t}^{portfolio} \tag{2.18}$$

where V_0 is the value of the initial investment, and $\emptyset(.)$ is the cumulative normal distribution.

The ES is given by:

$$ES_{s,t} = E[r_{s,t}^{portfolio} | r_{s,t}^{portfolio} \le VaR_{s,t}] \tag{2.19}$$

We calculated the means of oil-stock portfolio VaR and ES over different time scales and according to Eq. (2.17) we evaluated the downside risk reduction respectively as follows:

$$DRR_{s,t}^{VaR} = 1 - \frac{VaR^{portfolio}}{VaR^{stock}} \tag{2.20}$$

$$DRR_{s,t}^{ES} = 1 - \frac{ES^{portfolio}}{ES^{stock}} \tag{2.21}$$

Similar to the risk reduction Eq. (2.17), a higher value of $DRR_{s,t}$ means oil can diversify the downside risk better, Moreover, values of $DRR_{s,t}$ varying over different scales also implies an evolving risk reduction at different horizons.

Table 2.5 reports the results. We find that the values of downside risk reduction are almost bigger than zero in the high frequencies while those are negative in the low frequencies, meaning that the oil is useful in diversifying the downside risk in the short run and the benefits from oil diversification reduced over the long run. The result is consistent with the empirical results of Table 2.3 and 2.4, the higher interdependence between oil and stock for the long run implies higher risk and lower benefit. Look at the different stock markets, the risk reduction are best in the oil-Chinese stock and worst in the oil-Indonesian stock portfolio.

Insert Table 2.5 here

2.5 Conclusions

In our paper, we investigate the interdependence between oil and East Asian stock returns from 1992 to 2015. We also provide a fresh perspective on the analysis of oil-stock portfolio diversification allocation and risk management using the variance and covariance of wavelet coherence analysis.

We find that the independence between oil and stock returns for East Asian countries is almost homogenous while China and Japan have a weaker correlation with oil prices compared to other East Asian countries. This finding maybe attributed to domestic oil price controls by the Chinese government and a strong Japanese economy that is relatively invulnerable to oil prices. Moreover, considering five different sub-periods, the average coherency values are relatively higher in the crisis sub-periods of 1997 to 2001 and 2007 to 2011. Particularly, the average values in the short-term horizon during the former crisis period are almost the same as the other sub-periods while the values of the latter crisis period obviously increased, implying that the oil and East Asian stock markets experienced contagion effect during the global financial crisis period. Additionally, we find that oil and stock returns move in phase at all frequencies and oil prices lead to stock returns in the long-run cycle. In the medium and short-term scales, the phase difference with negative and positive values changes across scales. Particularly during the turmoil period, oil prices were lagging the stock market. Finally, from a financial perspective, the values of downside risk reduction are higher than zero in the high frequencies and negative in the low frequencies for all East Asian stock markets, which implies that the oil-stock portfolio can reduce the downside risk in the short term and provides evidence that the benefits of oil-stock portfolio diversification reduced over the long term horizon for East Asian markets.

Taken together, our findings suggest that for long-term investors, relatively high strength of co-movement in the long term reduces the diversification benefit between the involved assets while, for short-term investors, investment in crude oil is a good choice because of the low degree of correlation with stock returns; investors should only be concerned with increased co-movements during the crisis period, which suggests a high risk of contagion. For East Asian policy makers, understanding the relationships between oil prices and stock returns when they are leading or lagging can help governments devise sound policy measures to avoid financial market risk.

Table 2.1

Descriptive statistics of oil index and East Asian stock index returns.

	Oil	China	HK	Indonesia	Japan	Korea	Malaysia	Philippine	Singapore	Taiwan	Thailand
Observation	6210	6210	6210	6210	6210	6210	6210	6210	6210	6210	6210
Mean	5.861e-05	1.738e-04	1.167e-04	2.043e-04	-8.510e-06	8.373e-05	7.959e-05	1.261e-04	5.245e-05	4.381e-05	4.808e-05
Median	0	0	0	4.744e-05	0	0	0	0	0	0	0
Max	0.0713	0.3236	0.0749	0.0570	0.0559	0.0490	0.1010	0.0703	0.0477	0.0370	0.0493
Min	-0.0742	-0.0800	-0.0640	-0.0553	-0.0435	-0.0556	-0.1049	-0.0568	-0.0427	-0.0432	-0.0698
SD	0.0100	0.0106	0.0070	0.0064	0.0057	0.0074	0.0059	0.0060	0.0054	0.0063	0.0067
Normality test											
Skewness	-0.1771	5.5724	0.0316	-0.1995	-0.1902	-0.1650	0.7555	0.1945	-0.0080	-0.1345	0.0180
Kurtosis	8.286	159.061	12.757	12.371	9.054	8.562	54.584	13.765	10.063	6.212	10.684
Jarque-Bera	7.264***	6334.0***	24.636***	22.768***	9.521***	8.034***	689.11***	30.027***	12.91***	2.688***	15.278***

Note: HK presents Hong Kong; SD stands for standard deviation; Jarque-Bera correspond to the Jarque-Bera test statistics ($\times 10^{-3}$); *** Significance at 1% level respectively.

Table 2.2

Pearson correlation matrix.

	Oil	China	HK	Indonesia	Japan	Korea	Malaysia	Philippine	Singapore	Taiwan	Thailand
Oil	1										
China	0.0228	1									
HK	0.0917	0.1541	1								
Indonesia	0.0895	0.0855	0.4124	1							
Japan	0.0739	0.0987	0.4456	0.2971	1						
Korea	0.0648	0.0649	0.4056	0.2823	0.3772	1					
Malaysia	0.0421	0.0499	0.3686	0.3146	0.2420	0.2335	1				
Philippine	0.0396	0.0713	0.3446	0.3471	0.2663	0.2394	0.2565	1			
Singapore	0.0850	0.1009	0.6247	0.4500	0.4082	0.3995	0.4207	0.3328	1		
Taiwan	0.0562	0.0855	0.3571	0.2692	0.3193	0.3455	0.2159	0.2356	0.3605	1	
Thailand	0.0691	0.1042	0.4088	0.3667	0.2516	0.2989	0.3370	0.2938	0.4438	0.2272	1

Note: HK represents Hong Kong.

Table 2.3

Coherency and phase difference of oil and stock returns (China, Hong Kong, Indonesia, Japan, and South Korea) by sub periods.

	Days	China		Hong Kong		Indonesia		Japan		South Korea	
	frequency	Coherency	Phase	Coherency	Phase	Coherency	Phase	Coherency	Phase	Coherency	Phase
All period	2048-4096	0.2677	0.0150	0.2902	0.7160	0.4134	0.4854	0.3851	-0.1213	0.3251	0.1080
	1024-2048	0.2582	-0.8822	0.5381	0.0977	0.6668	-0.5894	0.5270	0.0387	0.5248	-0.2399
	512-1024	0.4019	-0.0649	0.6044	-0.3410	0.5942	-0.4617	0.4328	-0.6204	0.6614	-0.7324
	256-512	0.5251	0.3613	0.5747	-0.8683	0.4537	-0.5003	0.3482	-0.4373	0.5427	-0.8583
	128-256	0.3077	-0.2313	0.4037	-0.0058	0.3847	0.0373	0.3477	-0.0811	0.5178	-0.1386
January 1992-December-1996	2048-4096	0.2272	-0.6723	0.2811	1.1751	0.3955	0.8352	0.3498	0.3555	0.3225	0.3621
	1024-2048	0.3042	-0.5727	0.4591	-0.0602	0.6037	-0.8560	0.5510	-0.7860	0.5394	-0.3189
	512-1024	0.5004	-0.6899	0.5273	-0.2516	0.5021	-0.3602	0.3210	-0.6573	0.5807	-0.5742
	256-512	0.4052	-0.8781	0.4895	-1.0500	0.4482	-0.6198	0.2271	-0.3278	0.3030	-0.2680
	128-256	0.3203	-0.5101	0.3281	0.6561	0.3773	1.0568	0.2767	-0.2834	0.5938	0.0609
January 1997-December-2001	2048-4096	0.2478	-0.7221	0.2990	1.2224	0.4113	0.7201	0.3616	0.0428	0.3287	0.1239
	1024-2048	0.2745	-1.0493	0.6248	0.0537	0.7199	-0.7166	0.6517	-0.2160	0.6012	-0.2418
	512-1024	0.3196	-0.6832	0.6796	-0.2309	0.6629	-0.6486	0.5069	-0.3297	0.7716	-1.0096
	256-512	0.4453	-0.1847	0.6944	-1.6512	0.2692	-0.3310	0.3398	-0.3113	0.6560	-1.3292
	128-256	0.2512	-0.2065	0.3196	-0.9081	0.3412	-0.4505	0.4821	-0.7714	0.4469	-0.8964
January 2002-December-2006	2048-4096	0.2767	-0.0095	0.2989	0.8618	0.4211	0.4781	0.3898	-0.2451	0.3281	0.1928
	1024-2048	0.2459	-1.1196	0.6567	0.2413	0.7361	-0.3004	0.5928	0.2937	0.5883	0.1721
	512-1024	0.3076	0.6987	0.6329	-0.7277	0.6867	-1.1426	0.3109	-0.3982	0.6935	-1.1358
	256-512	0.6246	0.8108	0.4921	-0.9342	0.3582	-1.3622	0.2796	-0.8530	0.5007	-1.7012
	128-256	0.2734	-0.2336	0.3214	-0.2998	0.3167	-0.5099	0.2456	0.3195	0.3525	0.0905
January 2007-December-2011	2048-4096	0.2969	0.7097	0.2898	0.1747	0.4230	0.1705	0.4131	-0.3687	0.3258	-0.0476
	1024-2048	0.2467	-0.8884	0.5376	-0.1722	0.6735	-0.6165	0.4479	-0.2040	0.4930	-0.3652
	512-1024	0.5943	0.9446	0.7455	-0.6538	0.7342	-0.6507	0.5342	-0.8440	0.7512	-0.6370
	256-512	0.6944	0.9264	0.8248	-0.4603	0.8345	-0.6108	0.6313	-0.0865	0.8242	-0.5253

	128-256	0.3491	0.2083	0.5830	0.3428	0.4794	0.5245	0.4924	0.2592	0.6505	-0.0808
January 2012- October-2015	2048-4096	0.2968	1.0032	0.2795	-0.0308	0.4167	0.1417	0.4196	-0.4745	0.3191	-0.1529
	1024-2048	0.2075	-0.7489	0.3731	0.5282	0.5801	-0.4164	0.3495	1.4380	0.3641	-0.5098
	512-1024	0.2519	-0.7617	0.3842	0.3154	0.3197	0.7917	0.5089	-0.9514	0.4624	-0.1722
	256-512	0.4342	1.3704	0.3092	-0.0525	0.3282	0.7102	0.2365	-0.6613	0.3938	-0.3455
	128-256	0.3560	-0.4727	0.4858	0.2381	0.4162	-0.5813	0.2085	0.1173	0.5535	0.2176

Table 2.4

Coherency and phase difference of oil and stock returns (Malaysia, Philippine, Singapore, Taiwan, and Thailand) by sub periods.

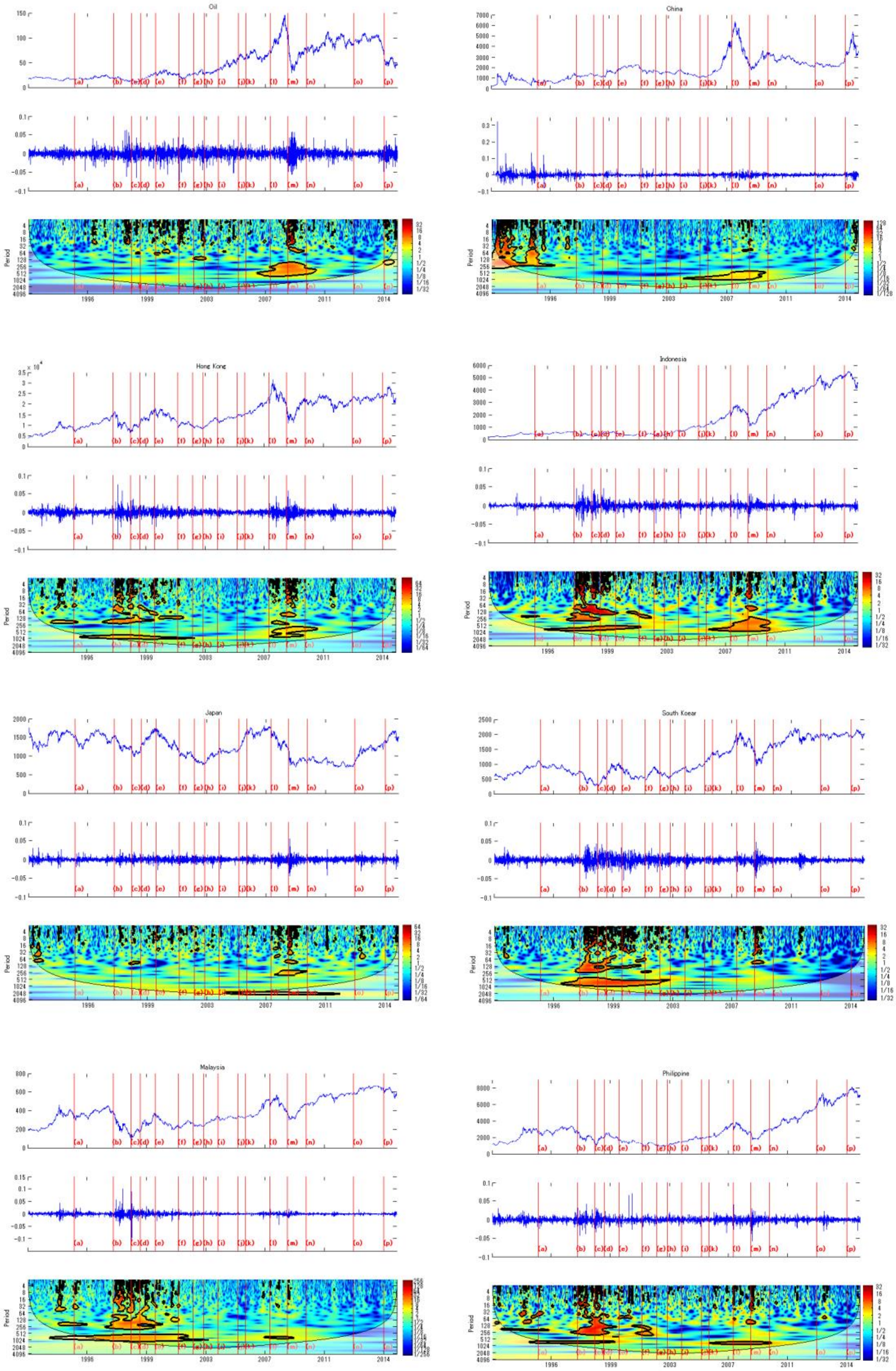
	Days	Malaysia		Philippine		Singapore		Chinese Taipei		Thailand	
	frequency	Coherency	Phase	Coherency	Phase	Coherency	Phase	Coherency	Phase	Coherency	Phase
	2048-4096	0.3114	0.0412	0.3673	0.6681	0.3555	0.5048	0.2442	1.0491	0.2163	0.0239
	1024-2048	0.4968	-0.1519	0.6031	-0.5004	0.6211	-0.0686	0.2962	-0.9550	0.5510	-0.7154
All period	512-1024	0.6939	-0.4448	0.5322	-0.7048	0.6338	-0.5310	0.4696	-0.2617	0.6462	-0.7409
	256-512	0.5113	-0.6116	0.4107	-0.4476	0.5230	-0.6016	0.5066	-0.5222	0.5277	-0.5547
	128-256	0.3892	0.2421	0.3990	0.1314	0.4406	-0.0985	0.4522	-0.3274	0.3986	0.2316
	2048-4096	0.3019	-0.6461	0.3444	0.9360	0.3331	0.7719	0.2316	1.8110	0.2016	0.2136
	1024-2048	0.4543	-0.7480	0.4816	-0.9578	0.5740	-0.2415	0.3088	-1.5494	0.5110	-0.4825
January 1992- December-1996	512-1024	0.5081	-0.1119	0.4450	-0.2391	0.4968	-0.4071	0.2975	0.2511	0.7606	-1.1067
	256-512	0.4758	0.5370	0.3247	-0.5021	0.5114	-1.1320	0.4373	-0.5101	0.6047	-0.9015
	128-256	0.5233	1.0293	0.3382	0.8811	0.4115	0.3503	0.3324	0.4375	0.4905	1.1201
	2048-4096	0.3047	-0.5521	0.3598	0.7927	0.3518	0.7147	0.2458	1.6138	0.2098	-0.0281
	1024-2048	0.5365	-0.3484	0.6254	-0.5762	0.6777	0.0625	0.3260	-1.5311	0.5644	-0.5013
January 1997- December-2001	512-1024	0.7708	-0.6453	0.5481	-1.1026	0.7263	-0.5446	0.3989	-0.0735	0.7488	-1.1337
	256-512	0.4297	-0.4351	0.4308	-0.5411	0.4446	-0.7720	0.2937	-0.2083	0.4402	-0.6530
	128-256	0.3137	0.0227	0.4262	-0.6588	0.2411	-0.3284	0.3536	-0.9016	0.2933	-0.1515
	2048-4096	0.3106	0.2036	0.3750	0.6961	0.3640	0.5548	0.2515	1.0531	0.2195	-0.1986
	1024-2048	0.5529	-0.1521	0.6803	-0.1552	0.7203	0.1494	0.3532	-0.7614	0.6057	-1.0886
January 2002- December-2006	512-1024	0.7630	-1.2169	0.6200	-1.4411	0.7117	-1.0979	0.5001	-1.0315	0.6165	-1.0187
	256-512	0.5131	-1.6169	0.3304	-1.1352	0.5884	-1.2811	0.5258	-1.6202	0.3712	-1.4209
	128-256	0.2709	-0.0168	0.3487	-0.4347	0.5571	-0.9641	0.4110	-0.7573	0.3607	-0.2293
	2048-4096	0.3202	0.6983	0.3824	0.2977	0.3673	0.2222	0.2495	0.3672	0.2269	0.0118
January 2007- December-2011	1024-2048	0.5081	-0.1014	0.6538	-0.4482	0.6916	-0.3211	0.2880	-0.7527	0.5806	-0.8559
	512-1024	0.8039	-0.9785	0.6759	-0.8529	0.7601	-0.7940	0.7280	-0.8297	0.7057	-0.5083
	256-512	0.7831	-0.7331	0.6519	-0.6217	0.4296	-0.2822	0.8998	-0.4609	0.8371	-0.4544

	128-256	0.3288	0.4131	0.5157	0.7963	0.3771	0.3286	0.6735	-0.1332	0.4806	0.1484
January 2012- October-2015	2048-4096	0.3218	0.6447	0.3774	0.6028	0.3636	0.1846	0.2421	0.1993	0.2261	0.1509
	1024-2048	0.4118	0.8210	0.5653	-0.3228	0.5911	0.0317	0.1767	0.0603	0.4754	-0.6278
	512-1024	0.6015	1.0956	0.3216	0.3672	0.7247	0.4136	0.4086	0.5745	0.3222	0.3129
	256-512	0.3057	-0.8707	0.2854	0.8774	0.8393	0.7893	0.3355	0.4096	0.3411	1.0336
	128-256	0.5471	-0.3869	0.3555	0.0549	0.6524	0.1896	0.5021	-0.2678	0.3582	0.2832

Table 2.5

Risk reduction effectiveness of oil-stock portfolio

Days frequency		China	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippine	Singapore	Chinese Taipei	Thailand
1-2 days	VaR	0.344	0.188	0.166	0.147	0.210	0.193	0.181	0.123	0.175	0.192
	ES	0.340	0.185	0.165	0.146	0.208	0.191	0.180	0.122	0.173	0.190
2-4 days	VaR	0.340	0.182	0.163	0.154	0.217	0.184	0.181	0.114	0.172	0.187
	ES	0.335	0.180	0.161	0.152	0.215	0.181	0.180	0.112	0.170	0.185
4-8 days	VaR	0.305	0.157	0.114	0.127	0.185	0.144	0.138	0.090	0.148	0.162
	ES	0.303	0.155	0.112	0.126	0.183	0.142	0.136	0.089	0.147	0.161
8-16 days	VaR	0.294	0.132	0.101	0.103	0.169	0.123	0.119	0.072	0.132	0.142
	ES	0.293	0.131	0.010	0.103	0.169	0.122	0.118	0.071	0.131	0.141
16-32 days	VaR	0.258	0.111	0.066	0.081	0.153	0.079	0.084	0.037	0.117	0.102
	ES	0.257	0.111	0.065	0.081	0.153	0.079	0.084	0.037	0.117	0.102
32-64 days	VaR	0.248	0.096	0.005	0.064	0.135	0.071	0.046	0.017	0.090	0.073
	ES	0.247	0.096	0.005	0.064	0.135	0.071	0.046	0.017	0.090	0.073
64-128	VaR	0.219	0.063	-0.062	0.065	0.123	-0.001	-0.002	0.002	0.070	0.069
days	ES	0.219	0.063	-0.063	0.065	0.122	-0.001	-0.002	0.002	0.070	0.069
128-256	VaR	0.173	0.096	-0.065	0.047	0.142	0.011	-0.028	0.041	0.049	0.063
days	ES	0.172	0.095	-0.065	0.047	0.142	0.011	-0.028	0.017	0.049	0.063
256-512	VaR	0.211	0.080	-0.101	0.021	0.068	-0.058	0.008	-0.076	0.040	0.032
days	ES	0.211	0.080	-0.101	0.021	0.068	-0.058	0.008	-0.076	0.040	0.032
512-1024	VaR	0.066	0.038	-0.044	0.041	0.110	-0.199	0.018	-0.111	0.011	0.043
days	ES	0.066	0.038	-0.044	0.041	0.110	-0.199	0.018	-0.111	0.011	0.043
1024-2048	VaR	-0.038	0.041	-0.150	-0.351	0.114	-0.219	-0.232	-0.149	-0.017	-0.292
days	ES	-0.038	0.041	-0.150	-0.352	0.114	-0.219	-0.232	-0.149	-0.017	-0.292
2048-4096	VaR	0.162	0.014	-0.382	0.058	0.037	-0.250	-0.306	-0.047	0.082	-0.175
days	ES	0.162	0.014	-0.382	0.058	0.037	-0.250	-0.306	-0.047	0.082	-0.175


Oil
China
Hong Kong
Indonesia
Japan
South Koear
Malaysia
Philippine
Period

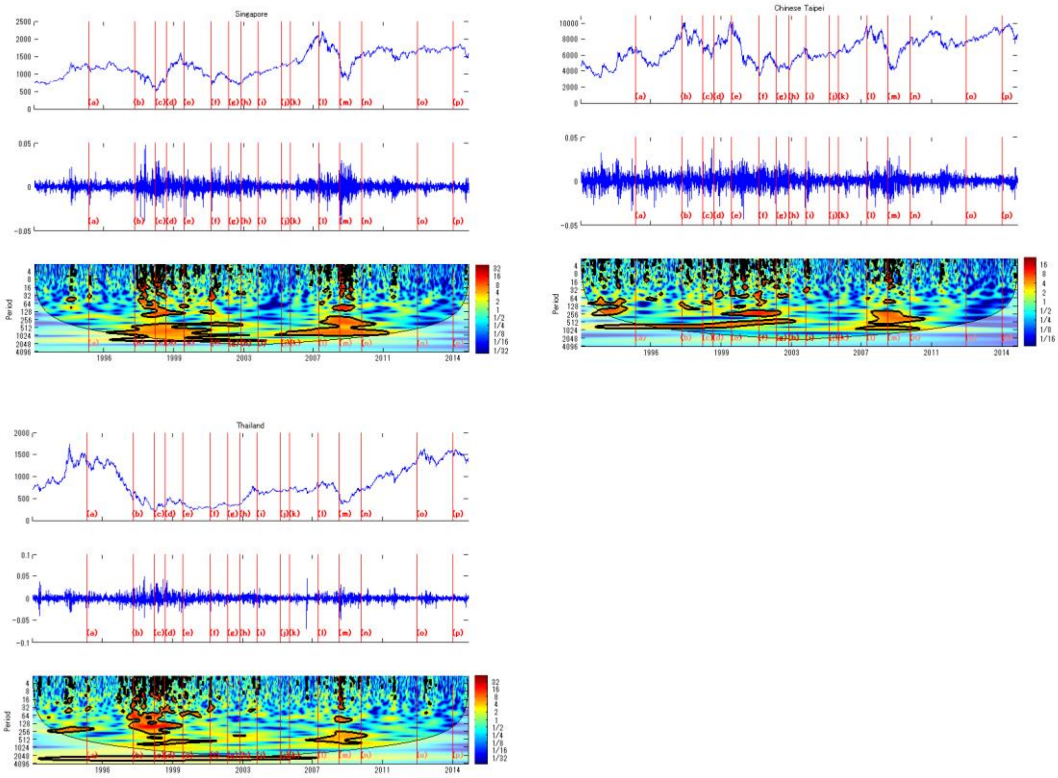
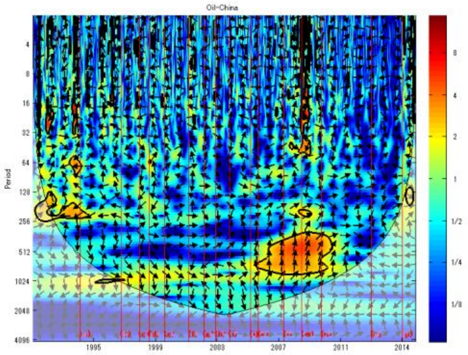
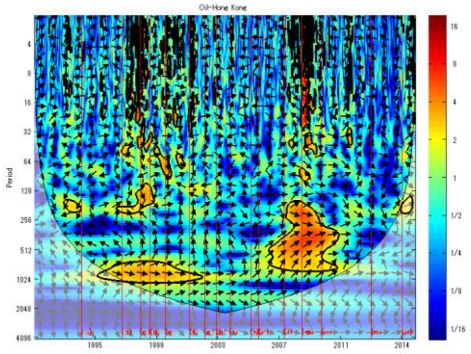
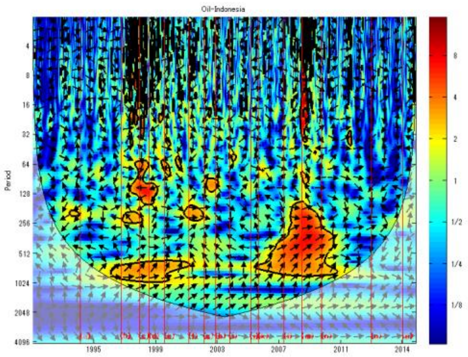


Fig.2.1. the WTI oil prices and the ten East Asian stock indexes (the top part), their returns (the medium part), and their continuous wavelet power spectrum (the bottom part) from January 2, 1992 to October 22, 2015.

Notes: special historical events are identified in the plots: (a) Mexican Peso crisis in December 1994; (b) Asian Financial Crisis in July 1997; (c) Russian Financial Crisis in August 1998; (d) oil production cuts by OPEC in March 1999; (e) Internet bubble in March 2000; (f) Terrorist Attacks in the USA in September 2001; (g) Stock market crash in August 2002; (h) Iraq War in May 2003; (i) Terrorist Attacks of Madrid in March 2004; (j) London bombings in July 2005; (k) OPEC cut oil production in November 2006; (l) Sub-prime crisis in August 2007; (m) Global financial collapse in September 2008; (n) European sovereign debt crisis; (o) U.S. debt-ceiling crisis in January 2013; (p) Russian financial crisis in December 2014.


Oil-China
Period
1995
1999
2003
2007
2011
2014


Oil-Hong Kong
Period
1995
1999
2003
2007
2011
2014


Oil-Indonesia
Period
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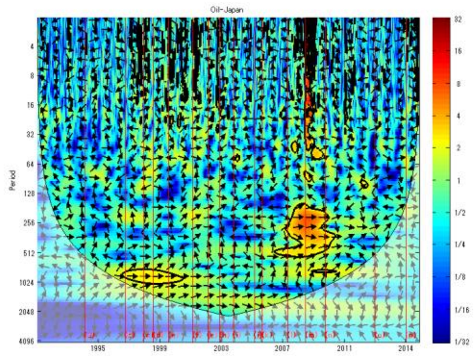
1999
2003
2007
2011
2014


Oil-Japan
Period
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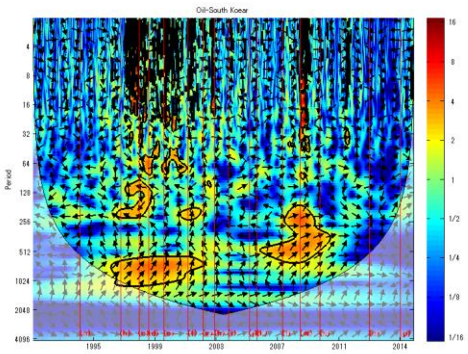
1999
2003
2007
2011
2014


Oil-South Koear
Period
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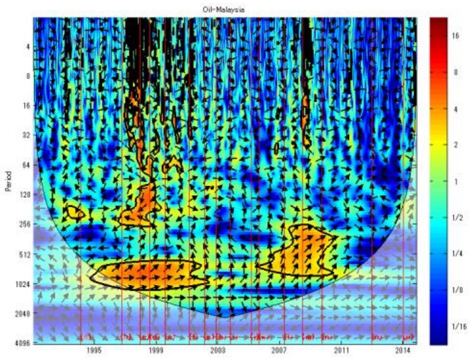
2011
2014


Oil-Malaysia
Period
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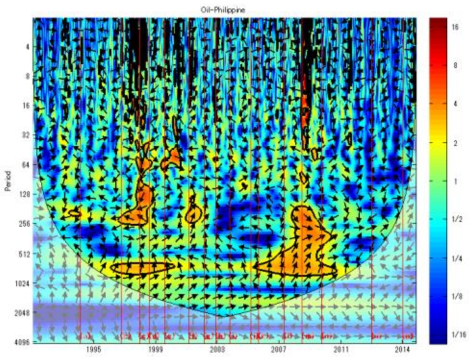
1999
2003
2007
2011
2014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Period
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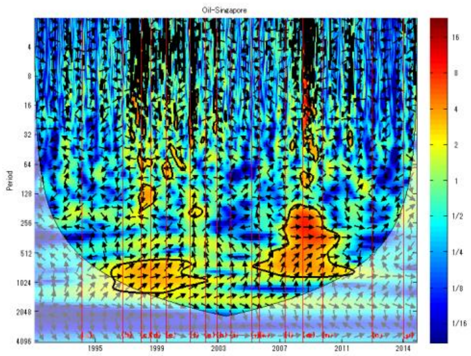
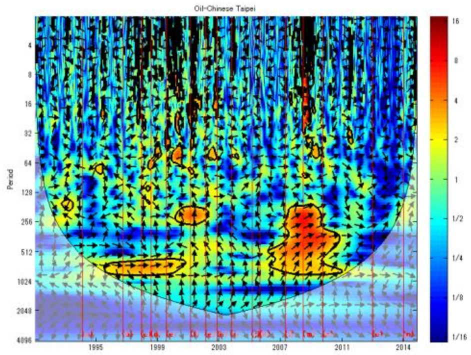
1999
2003
2007
2011
2014


Oil-Singapore
Period
1995
1999
2003
2007
2011
2014



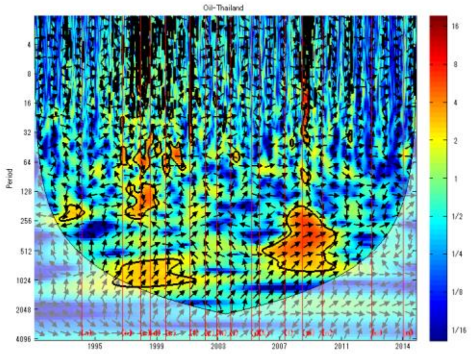
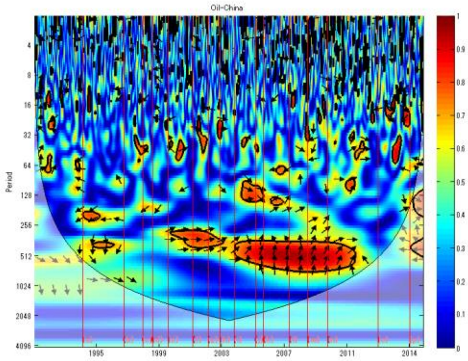
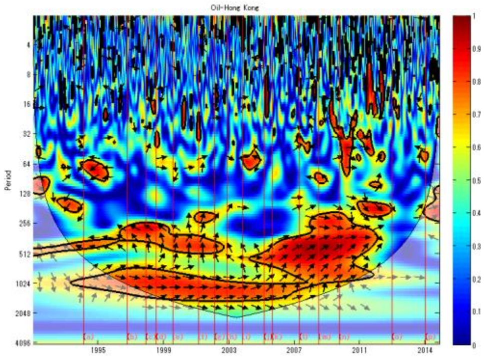
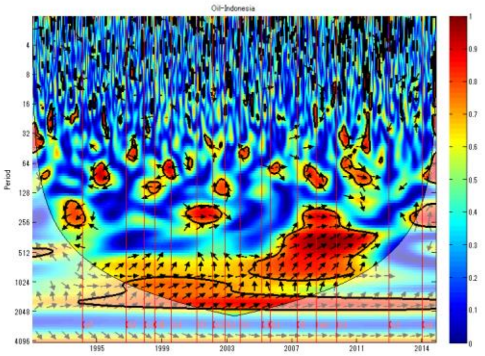


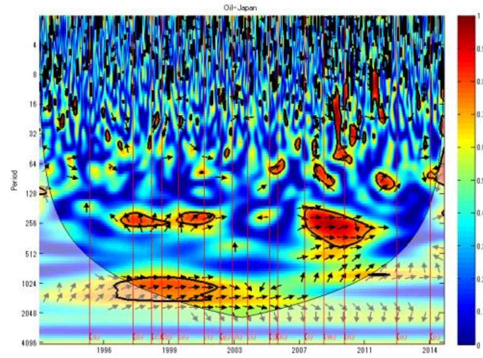
Fig.2.2. Cross-wavelet transform between oil and East Asian stock markets for the period January 2, 1992 to October 22, 2015.

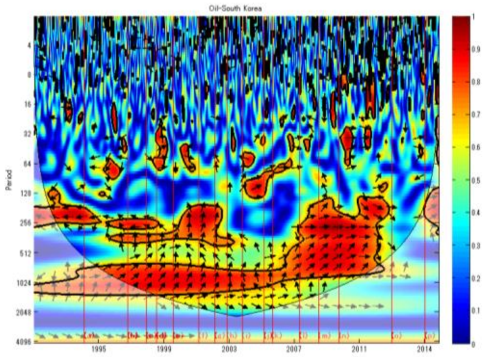
Notes: special historical events are identified in the plots: (a) Mexican Peso crisis in December 1994; (b) Asian Financial Crisis in July 1997; (c) Russian Financial Crisis in August 1998; (d) oil production cuts by OPEC in March 1999; (e) Internet bubble in March 2000; (f) Terrorist Attacks in the USA in September 2001; (g) Stock market crash in August 2002; (h) Iraq War in May 2003; (i) Terrorist Attacks of Madrid in March 2004; (j) London bombings in July 2005; (k) OPEC cut oil production in November 2006; (l) Sub-prime crisis in August 2007; (m) Global financial collapse in September 2008; (n) European sovereign debt crisis; (o) U.S. debt-ceiling crisis in January 2013; (p) Russian financial crisis in December 2014.

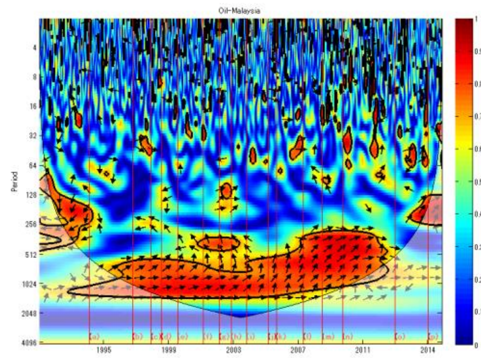

Oil-China
Period
1995 1999 2003 2007 2011 2014

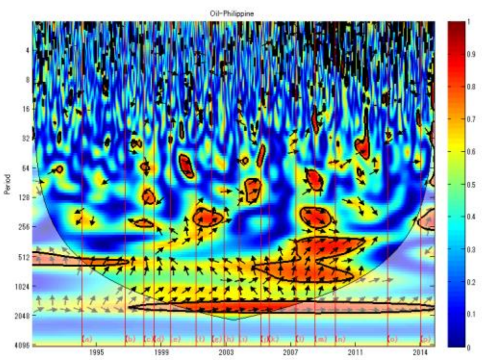

Oil-Hong Kong
Period
1995 1999 2003 2007 2011 2014

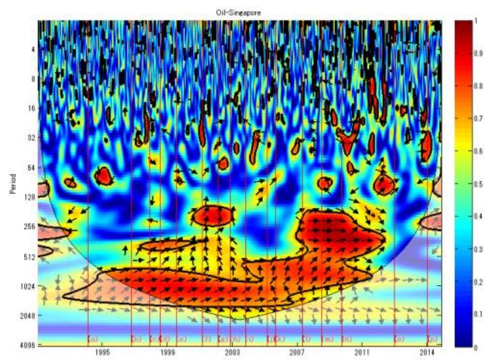

Oil-Indonesia
Period
1995 1999 2003 2007 2011 2014


Oil-Japan
Period
1995 1999 2003 2007 2011 2014


Oil-South Korea
Period
1995 1999 2003 2007 2011 2014


Oil-Malaysia
Period
1995 1999 2003 2007 2011 2014


Oil-Philippine
Period
1995 1999 2003 2007 2011 2014


Oil-Singapore
Period
1995 1999 2003 2007 2011 2014

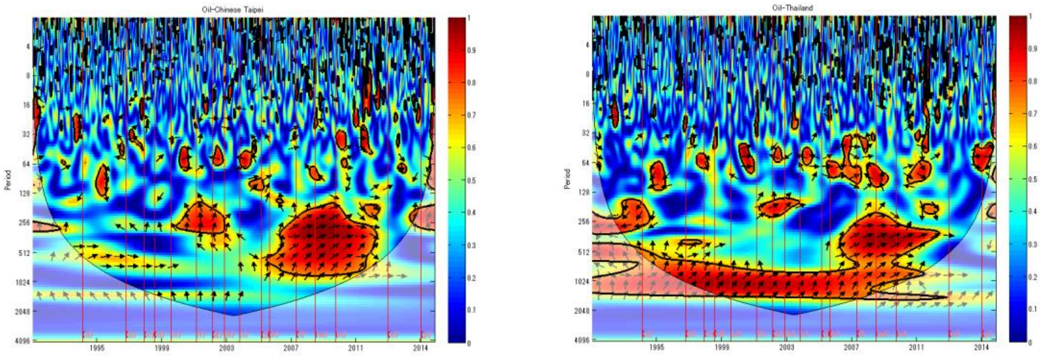
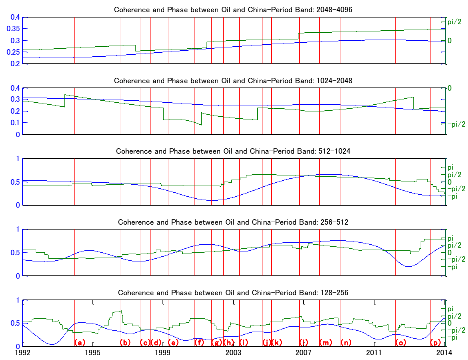


Fig.2.3. Wavelet coherence plot between oil and East Asian stock markets from January 2, 1992 until October 22, 2015.

Notes: special historical events are identified in the plots: (a) Mexican Peso crisis in December 1994; (b) Asian Financial Crisis in July 1997; (c) Russian Financial Crisis in August 1998; (d) oil production cuts by OPEC in March 1999; (e) Internet bubble in March 2000; (f) Terrorist Attacks in the USA in September 2001; (g) Stock market crash in August 2002; (h) Iraq War in May 2003; (i) Terrorist Attacks of Madrid in March 2004; (j) London bombings in July 2005; (k) OPEC cut oil production in November 2006; (l) Sub-prime crisis in August 2007; (m) Global financial collapse in September 2008; (n) European sovereign debt crisis; (o) U.S. debt-ceiling crisis in January 2013; (p) Russian financial crisis in December 2014.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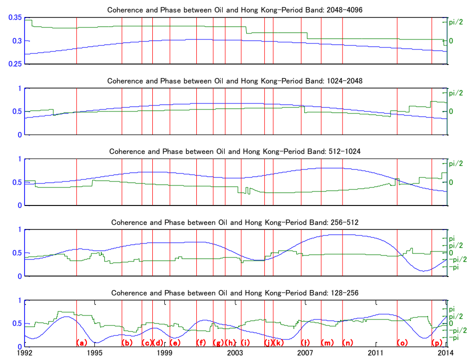
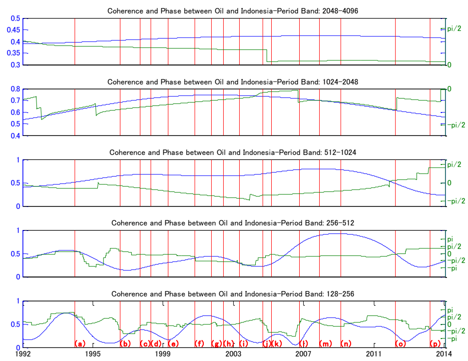
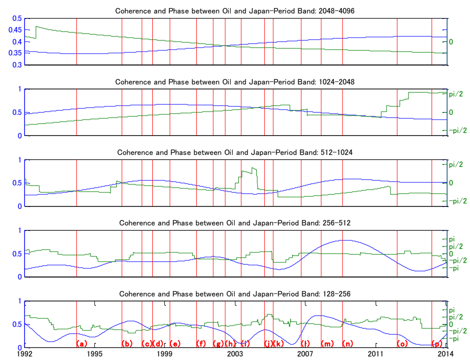
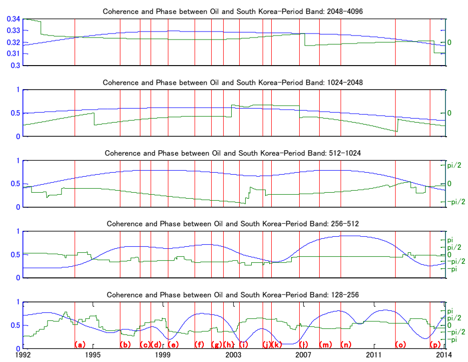
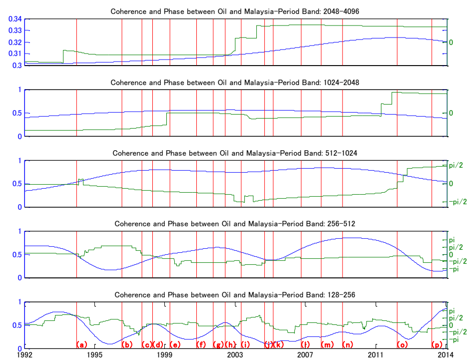
Coherence and Phase between Oil and China-Period Band: 1024-2048
Coherence and Phase between Oil and China-Period Band: 512-1024
Coherence and Phase between Oil and China-Period Band: 256-512
Coherence and Phase between Oil and China-Period Band: 128-256

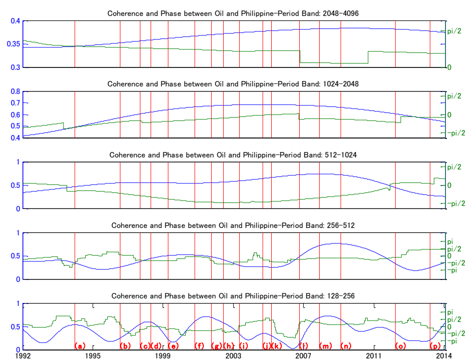

Coherence and Phase between Oil and Hong Kong-Period Band: 2048-4096
Coherence and Phase between Oil and Hong Kong-Period Band: 1024-2048
Coherence and Phase between Oil and Hong Kong-Period Band: 512-1024
Coherence and Phase between Oil and Hong Kong-Period Band: 256-512
Coherence and Phase between Oil and Hong Kong-Period Band: 128-256


Coherence and Phase between Oil and Indonesia-Period Band: 2048-4096
Coherence and Phase between Oil and Indonesia-Period Band: 1024-2048
Coherence and Phase between Oil and Indonesia-Period Band: 512-1024
Coherence and Phase between Oil and Indonesia-Period Band: 256-512
Coherence and Phase between Oil and Indonesia-Period Band: 128-256


Coherence and Phase between Oil and Japan-Period Band: 2048-4096
Coherence and Phase between Oil and Japan-Period Band: 1024-2048
Coherence and Phase between Oil and Japan-Period Band: 512-1024
Coherence and Phase between Oil and Japan-Period Band: 256-512
Coherence and Phase between Oil and Japan-Period Band: 128-256


Coherence and Phase between Oil and South Korea-Period Band: 2048-4096
Coherence and Phase between Oil and South Korea-Period Band: 1024-2048
Coherence and Phase between Oil and South Korea-Period Band: 512-1024
Coherence and Phase between Oil and South Korea-Period Band: 256-512
Coherence and Phase between Oil and South Korea-Period Band: 128-256


Coherence and Phase between Oil and Malaysia-Period Band: 2048-4096
Coherence and Phase between Oil and Malaysia-Period Band: 1024-2048
Coherence and Phase between Oil and Malaysia-Period Band: 512-1024
Coherence and Phase between Oil and Malaysia-Period Band: 256-512
Coherence and Phase between Oil and Malaysia-Period Band: 128-256


Coherence and Phase between Oil and Philippine-Period Band: 2048-4096
Coherence and Phase between Oil and Philippine-Period Band: 1024-2048
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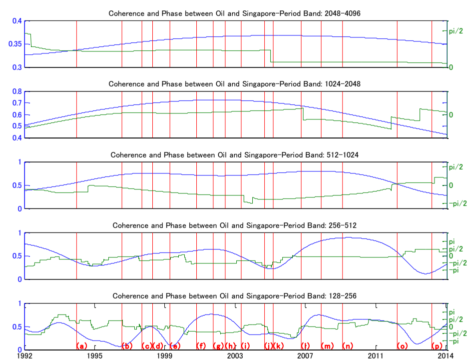

Coherence and Phase between Oil and Singapore-Period Band: 2048-4096
Coherence and Phase between Oil and Singapore-Period Band: 1024-2048
Coherence and Phase between Oil and Singapore-Period Band: 512-1024
Coherence and Phase between Oil and Singapore-Period Band: 256-512
Coherence and Phase between Oil and Singapore-Period Band: 128-256

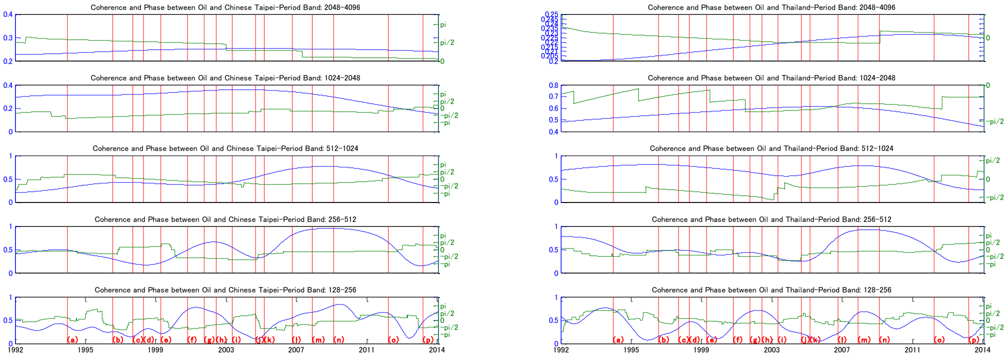
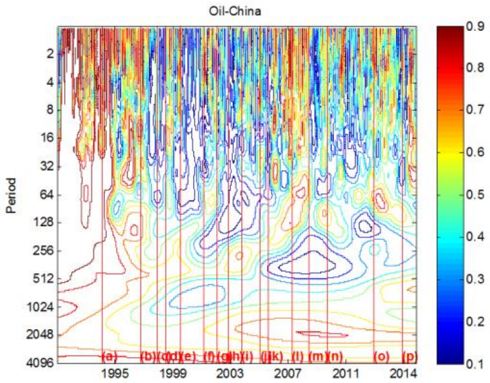
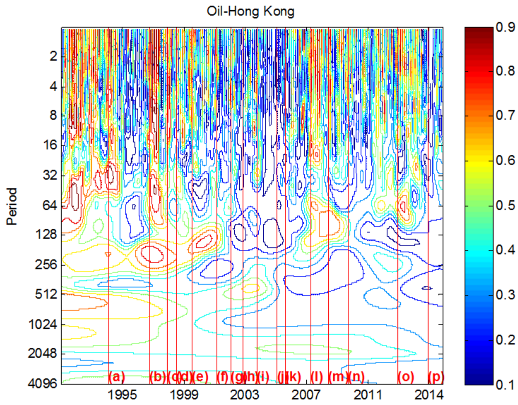
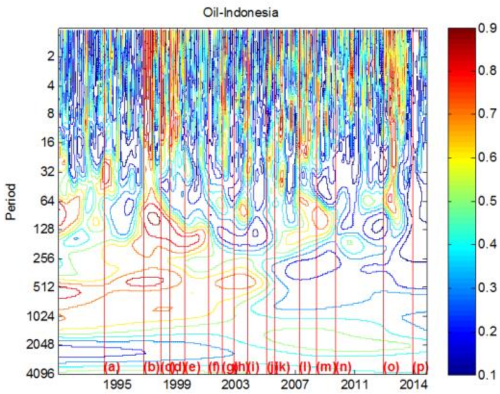


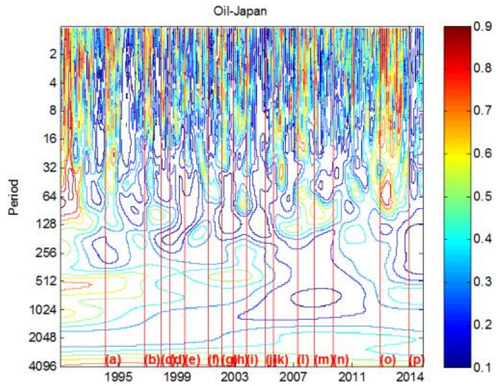
Fig.2.4. Wavelet coherency (left vertical axis and the blue line) and phase difference (right vertical axis and the green line) between oil and East Asian stock returns.

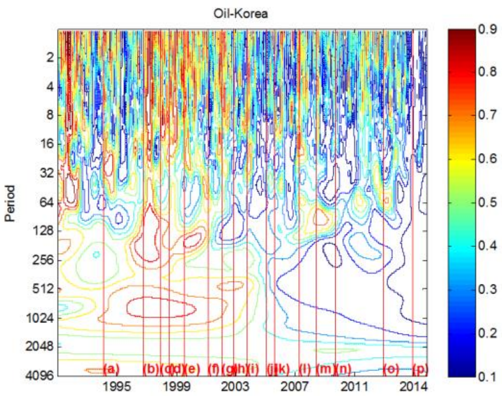
Notes: special historical events are identified in the plots: (a) Mexican Peso crisis in December 1994; (b) Asian Financial Crisis in July 1997; (c) Russian Financial Crisis in August 1998; (d) oil production cuts by OPEC in March 1999; (e) Internet bubble in March 2000; (f) Terrorist Attacks in the USA in September 2001; (g) Stock market crash in August 2002; (h) Iraq War in May 2003; (i) Terrorist Attacks of Madrid in March 2004; (j) London bombings in July 2005; (k) OPEC cut oil production in November 2006; (l) Sub-prime crisis in August 2007; (m) Global financial collapse in September 2008; (n) European sovereign debt crisis; (o) U.S. debt-ceiling crisis in January 2013; (p) Russian financial crisis in December 2014.

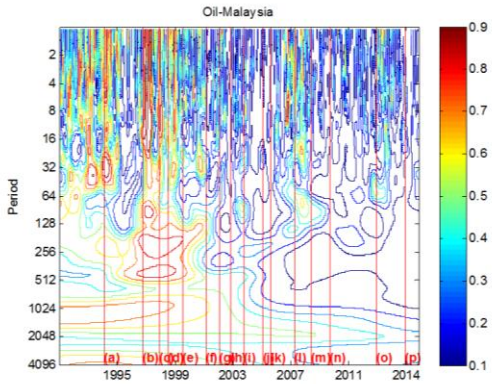

Oil-China
Period

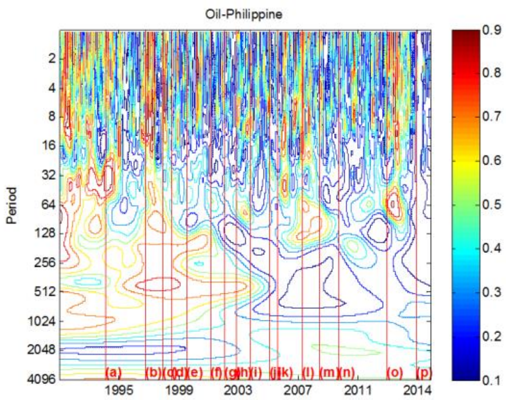

Oil-Hong Kong
Period

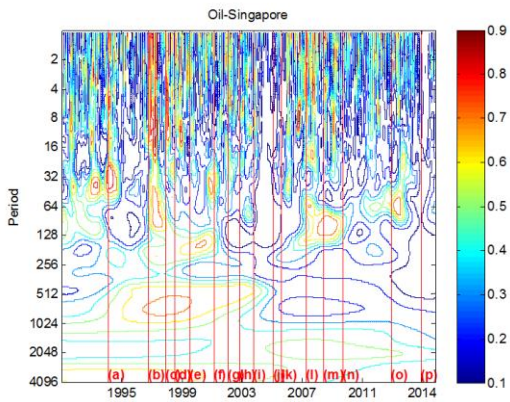

Oil-Indonesia
Period


Oil-Japan
Period


Oil-Korea
Period


Oil-Malaysia
Period


Oil-Philippine
Period


Oil-Singapore
Period

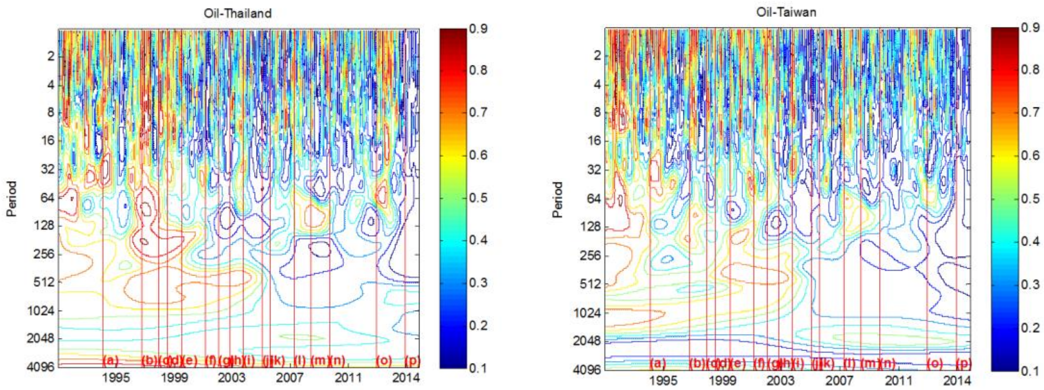


Fig.2.5. Risk reduction in the oil-stock portfolio variance from January 2, 1992 until October 22, 2015.

Notes: special historical events are identified in the plots: (a) Mexican Peso crisis in December 1994; (b) Asian Financial Crisis in July 1997; (c) Russian Financial Crisis in August 1998; (d) oil production cuts by OPEC in March 1999; (e) Internet bubble in March 2000; (f) Terrorist Attacks in the USA in September 2001; (g) Stock market crash in August 2002; (h) Iraq War in May 2003; (i) Terrorist Attacks of Madrid in March 2004; (j) London bombings in July 2005; (k) OPEC cut oil production in November 2006; (l) Sub-prime crisis in August 2007; (m) Global financial collapse in September 2008; (n) European sovereign debt crisis; (o) U.S. debt-ceiling crisis in January 2013; (p) Russian financial crisis in December 2014.

Chapter 3

Modelling interdependence between East Asian stock markets and the prices of oil and gold: a wavelet based approach

3.1 Introduction

Crude oil is maybe the most strategic commodity which is widely considered to affect the real economy and financial markets worldwide. Precious metals are also strategic commodities with increased prices recently. Particularly, gold is an important precious metal and plays a role as a safe haven in periods of political and economic instability. The volatility and influence of oil and gold prices has become crucial for world economic development. On the other hand, their prices not only have concerned with the macroeconomic but also became a critical part in financial field. Recent studies suggest that lower diversification benefits from equity investment due to the increased correlations between equity markets particularly during the high volatility periods (Diamandis 2009). This fact provides investors with new ways to diversify their investment portfolios. Owing to differing volatile returns and low correlations between commodity and stock markets, crude oil and gold have become additional investment tools for international portfolio diversification between stocks, bonds, and currencies (Arouri et al. 2013; Daskalaki and Skiadopoulos 2011). Particularly, over the last decade, crude oil and gold prices have increased sharply and have exhibited high volatility.

Investing in oil and gold is seen as a way to further diversify risk and hedge against inflation. Therefore, analyzing price co-movements between oil, gold and stock markets is an essential component of modern finance because effective investigation of volatility and correlation are needed for derivative pricing, portfolio optimization, risk management, and herding.

In our paper, we investigate the interdependence between East Asian stock markets and the prices of crude oil and gold. Many literatures have examined the oil-stock relationship for main developed countries (Avdulaj and Barunik, 2015) while few studies focus on how it works for East Asian stock markets. In fact, this is an interesting and important subject. Over the previous decades, East Asian has emerged as the world's fastest growing regional economy and become one of the three core economic regions (along with Europe and North America) (Dent 2013). The region's miraculous economic growth and dynamism has become a popular topic for academic and business research (Cai and Hamori, 2015). Furthermore, East Asia includes three of the world's top ten oil-importing nations –China (China represents Chinese mainland in our paper), Japan, and South Korea. Each of these three nations, as well as other nations in East Asia, shows an increasing demand for oil. Additionally, the majority of East Asian oil imports are from the volatile Middle East, and there has been no regional mechanism in East Asia to stockpile emergency petroleum supplies (Shin and Savage, 2011), which makes East Asia highly susceptible to oil shocks such as the 2003 Iraq invasion or the 2006 OPEC cut agreement. Therefore, changes in crude oil prices had a greater impact on East Asian economies than developed countries.

Moreover, the risk reduction benefit from diversification has been a major subject in the financial literature for decades. Particularly, East Asian stock markets suffered huge losses in the periods of 1997 Asian and 2008 global turmoil. It is important to finding useful investment tools to diversify risk and hedge for international investors and East Asian policy makers. Although the idea of utilizing crude oil as a diversification tool for financial assets attracted many literatures, we found no consensus regarding their linkage. Fratzscher et al., (2014) conclude that oil is a nearly perfect diversification tool for stocks due to their null, or even negative correlation. However, Avdulaj and Barunik (2015) find decreasing benefits of oil in stock portfolios over the past ten years. The majority of empirical studies use linear correlations that ignore asymmetric and possible non-linear tail dependence. Despite this, another limitation of the previous empirical studies is that they are restricted to one or, at most, two time scales – the short and long term. In fact, international investors should be heterogeneous with respect to their different investment horizons.

In this study we investigate the interdependence between East Asian stock markets and the prices of oil and gold in different time scales by using the conditional copula functions and wavelet transform analysis. We offer two contributions. First, we use the conditional copula functions introduced by Patton (2006) to capture the joint distributions of pairs without losing the asymmetric and non-linear tail dependence. Second, we employ the wavelet analysis that offers a huge advantage in that it provides a framework to measure the frequency components of dynamic movement without losing time-specific information. We decompose the estimated standardized residuals obtained from the marginal distribution process up to 6 levels, covering short-term, midterm, and long-term horizons and then examine their interdependence on a scale by scale basis.

The remainder of the article is organized as follows. Section 2 introduces the model specification for the marginal distributions, wavelet transform and the conditional copula functions. Section 3 describes our data. In section 4, we discuss our empirical results. Section 5 concludes.

3.2 Model specification

Our modelling strategy utilizes the wavelet transform to decompose the standardized residuals across different time horizons and recently proposed dynamic copula to capture their interdependence.

Patton (2006) extended the theorem of Sklar (1959) to the conditional copula which states that a conditional joint distribution can be decomposed into different conditional marginal distributions and a conditional copula function.

Consider the bivariate stochastic process $X_t = (x_{1t}, x_{2t})'$ with a conditional joint distribution F and conditional marginal distributions F_1 and F_2.

$$F\,(X_t|\mathcal{F}_{t-1}) = C\,(F_1(x_{1t}|\mathcal{F}_{t-1}), F_2(x_{2t}|\mathcal{F}_{t-1})|\mathcal{F}_{t-1}) \quad (3.1)$$

where C is the conditional copula of X_t and $\mathcal{F}_{t-1}$ is the information set. Due to Patton (2006), we can model dynamic dependence between two assets by linking together two different marginal distributions with a copula function that provides a lot of flexibility in modeling the joint distributions.

3.2.1 Marginal distribution

We first model the conditional marginal distribution for different asset markets respectively.

$$y_{i,t} = \mu_i(Y_{t-1}, \phi) + \sigma_{i,t}(Y_{t-1}, \alpha) z_{i,t}, \;\; Y_{t-1} \in \mathcal{F}_{t-1} \quad (3.2)$$

$z_{i,t}|\mathcal{F}_{t-1} \sim F_i(0,1)$

where μ_i is the conditional mean and $\sigma_{i,t}$ is the conditional standardized variance which have been considered by a wide variety of models. In our paper, we assume that the AR and GARCH-type models for the conditional mean and variance. ϕ and α are the vector of parameters for the conditional mean and variance models.

in our paper we use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to determine the AR order p and consider the volatility models in the GJR-GARCH (1, 1, 1) process, see Glosten et al. (1993).

$$y_{i,t} = \phi_{0,i} + \sum_j \phi_{j,i} y_{i,t-j} + \varepsilon_{i,t}, i = 1, \dots, n \tag{3.3}$$

$$\varepsilon_{i,t} = z_{i,t}\sigma_{i,t},\ z_{i,t}|\mathcal{F}_{t-1} \sim (0,1)$$

$$\sigma_{i,t}^2 = \omega_i + \beta_i \sigma_{i,t-1}^2 + \alpha_i {\varepsilon_{i,t-1}}^2 + \gamma_i {\varepsilon_{i,t-1}}^2 I_{i,t-1} \tag{3.4}$$

where $\phi_{0,i}$ is the constant mean, $\sigma_{i,t}^2$ is the conditional variance, $\omega_i > 0$, $\alpha_i, \beta_i, \gamma_i \geq 0$, $I_{i,t-1}$ is equal to 1 when $\varepsilon_{i,t-1} < 0$ and 0 otherwise.

We assume that the standardized residuals $z_{i,t}$ follow skew-t distribution of Hansen (1994) as follows:

$$d(z|\eta,\lambda) = \begin{cases} bc(1 + \frac{1}{\eta-2}(\frac{bz+a}{1-\lambda})^2)^{-\frac{\eta+1}{2}} if\ z < -\frac{a}{b} \\ bc(1 + \frac{1}{\eta-2}(\frac{bz+a}{1+\lambda})^2)^{-\frac{\eta+1}{2}} if\ z \geq -\frac{a}{b} \end{cases} \tag{3.5}$$

where $a \equiv 4\lambda c \frac{\eta-2}{\eta-1}$, $b^2 \equiv 1 + 3\lambda - a^2$, and $c \equiv \frac{\Gamma(\frac{\eta+1}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})}$. λ and η are the skewness parameter and degree of freedom parameter, respectively. An inspection of the various formulas reveals that this density is defined for $2 < \eta < \infty$ and $-1 < \lambda < 1$. If $\lambda = 0$, Hansen's skewed Student's t-distribution is then reduced to the traditional Student's t-distribution, which is not skewed. If, in addition, $\eta \to \infty$, the Student's t-distribution collapses to the normal density.

Therefore, we obtain the estimated standardized residuals $\hat{z}_{i,t}$ as

$$\hat{z}_{i,t} = \frac{y_{i,t} - \hat{\phi}_{0,i} + \sum_j \hat{\phi}_{j,i} y_{i,t-j}}{\hat{\sigma}_{i,t}} \tag{3.6}$$

where $\hat{\phi}_{0,i}$, $\hat{\phi}_{j,i}$ and $\hat{\sigma}_{i,t}$ are the estimated parameters for the models for the conditional mean and conditional variance.

3.2.2 Multiresolution analysis

We then use the wavelet transform analysis to decompose the estimated standardized residuals with different frequencies. Thus, we can capture the dynamics of the series across different time horizons (short-, medium-, and long-term).

Wavelet analysis relies on two basic functions: father wavelet and mother wavelet. Father wavelet ϕ can enhance the representation of the trending for a signal while mother wavelet ψ can describe the details or fluctuations of the signal. They are formally defined as follows:

$$\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi\left(2^{-j}t - k\right), j = 1, \ldots, J \tag{3.7}$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(2^{-j}t - k\right),, j = 1, \ldots, J \tag{3.8}$$

where j is the scaling parameter that controls the degree of stretching of the function, meaning that the bigger j presents the more stretched of the wavelet transform function. k is the translation parameter which implies that the wavelet functions with the larger k transform the higher frequency signal much better.

We then take the wavelet coefficient calculation using the wavelet functions and decompose the original series into the wavelet smooth and the wavelet detail. In our paper, we represent the multiresolution representation of the estimated standardized residuals by:

$$z(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\,\psi_{J,k}(t) + \sum_k d_{J-1,k}\,\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\,\psi_{1,k}(t)$$

$$= S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t)$$

$$S_J = \sum_k s_{J,k}\phi_{J,k}(t)$$

$$D_J = \sum_k d_{J,k}\psi_{J,k}(t) \tag{3.9}$$

where the coefficients $s_{J,k}$, $d_{J,k}, \ldots,$ $d_{1,k}$ are the wavelet transform coefficients which can be approximated by $s_{J,k} = \sum_k \phi_{J,k} z(t), d_{J,k} = \sum_k \psi_{J,k} z(t)$. The capital S_J and D_J are the wavelet smooth and detail. The wavelet smooth S_J provides the approximated trend while the wavelet detail D_J captures the local volatility over the different time horizons 2^J days. In our empirical analysis, we use the daily data and choose $J = 5$ to measure the local volatility over 2 days (daily effect), 4 days (weekly effect), 8 days, 16 days (monthly effect), 32 days, respectively.

Specifically, in our paper we compute the wavelet coefficient by applying the maximal overlap discrete wavelet transform (MODWT) that overcome the dyadic length sample size restriction of discrete wavelet transform.

3.2.3 Copula functions

Next, we measure the dependence structure between two assets by using the conditional copula functions that is the conditional distribution of the probability integral transforms of the standardized residuals. Thus we consider the copula functions.

$$U_{it}|\mathcal{F}_{t-1} = F_i^{skewt}(z_{i,t}) \tag{3.10}$$

$$U_t|\mathcal{F}_{t-1} = \{U_{1t}, U_{2t}\}'|\mathcal{F}_{t-1} \sim C(\kappa) \tag{3.11}$$

where κ is the parameter of the copula.

We choose five different copula functions to consider both symmetric and asymmetric dependence structures including Normal copula, Student's t copula, Clayton copula, Rotated Gumbel copula and Symmetrized Joe-Clayton (SJC) copula.

The Normal copula can be written as:

$$C^N(u,v;\ \rho) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} exp\{-\frac{r^2+s^2-2\rho rs}{2(1-\rho^2)}\} drds \tag{3.12}$$

where $\rho \in (-1,1)$ is simply the linear correlation coefficient between the two random variables. Φ^{-1} is the inverse of standard normal distribution. $\rho = 0$ implies the independence copula. We note that the lower and upper tail dependence of Normal copula is zero.

The bivariate Student's t copula has the following analytic form:

$$C^t(u,v;\ \rho,\eta) = \int_{-\infty}^{t^{-1}(u)} \int_{-\infty}^{t^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \{1 + \frac{r^2+s^2-2\rho rs}{\omega(1-\rho^2)}\}^{-\frac{2+\eta}{2}} drds \qquad (3.13)$$

where $\rho \in (-1,1)$ is the linear correlation coefficient of the bivariate Student's t distribution with η degrees of freedom. t^{-1} is the inverse of Student's t distribution. The lower tail dependence of Student's t copula is equal to the upper tail dependence.

The bivariate Clayton copula is defined as

$$C^{Cl}(u,v;\ \kappa) = (u^{-\kappa} + v^{-\kappa} - 1)^{-\frac{1}{\kappa}} \qquad (3.14)$$

where $0 < \kappa < \infty$. $\kappa \to 0$ means the independence copula. The Clayton copula are asymmetric and only has lower tail dependence.

The bivariate Rotated Gumbel copula is defined by

$$C^{Gu}(u,v;\ \kappa) = exp(-[(-\ln(1-u))^{\kappa} + (-\ln(1-v))^{\kappa}]^{\frac{1}{\kappa}}) \qquad (3.15)$$

where $1 < \kappa < \infty$. $\kappa \to 1$ means the independence copula. The Rotated Gumbel copula are asymmetric and only has lower tail dependence.

The Symmetrized Joe-Clayton (SJC) copula is obtained from the linear combination of the Joe-Clayton copula (C^{JC}).

$$C^{SJC}(u,v;\ \tau^L,\tau^U) = 0.5 * (C^{JC}(u,v;\ \tau^L,\tau^U) + C^{JC}(1-u,1-v;\ \tau^L,\tau^U) + u + v - 1)$$

(3.16)

$$C^{JC}(u,v;\ \tau^L,\tau^U) = 1 - (1 - \{\left[1-(1-u)^{\frac{1}{log_2(2-\tau^U)}}\right]^{-\frac{1}{log_2\tau^L}} + \left[1-(1-v)^{\frac{1}{log_2(2-\tau^U)}}\right]^{-\frac{1}{log_2\tau^L}} - 1\}^{log_2\tau^L})^{log_2(2-\tau^U)}$$

(3.17)

where the two parameters $\tau^L \in (0,1)$ and $\tau^U \in (0,1)$ representing the lower and upper tail dependence respectively.

3.2.4 Estimation

The estimation method is multi-stage maximum likelihood (MSML) that first estimates the marginal distributions and then estimating the copula parameters conditioning on the estimated marginal distribution parameters.

The log-likelihood specification is given by

$$\log\mathcal{L}(\theta) = \sum_{t=1}^{T} \log f_t(y_t;\ \theta) =$$

$$\sum_t \log f_{1t}\left(y_{1,t};\ \phi,\alpha\right) + \sum_t \log f_{2t}\left(y_{2,t};\ \phi,\alpha\right) + \sum_t \log c(F_{1t}\left(y_{1,t};\ \phi,\alpha\right), F_{2t}\left(y_{2,t};\ \phi,\alpha\right);\kappa) \tag{3.18}$$

where $\theta = (\phi',\alpha',\kappa')'$ is the parameter for the entire model. The log–likelihood is decomposed into two parts, with the first two terms related to the marginal estimation and the last term related to the copula. Then, we maximize the likelihood simultaneously over all parameters of θ. First, we obtain the marginal estimations.

$$\hat{\phi},\hat{\alpha} = \operatorname{argmax} \sum_t \log f_{it}\left(y_{i,t};\ \phi,\alpha\right) \tag{3.19}$$

Second, the dependency parameter of the copula function can be obtained by

$$\hat{\kappa} = \operatorname{argmax} \sum_t \log c(F_{1t}\left(y_{1,t};\ \hat{\phi},\hat{\alpha}\right), F_{2t}\left(y_{2,t}; \hat{\phi},\hat{\alpha}\right);\kappa) \tag{3.20}$$

3.3 Data

The data set used in this paper consists of daily prices of oil and gold and East Asian stock market indexes. We use the West Texas Intermediate (WTI) Cushing Crude Oil Spot Price Index for oil prices and London Bullion Market Association (LBMA) Gold Price Index for gold prices. For East Asian stock markets, we choose 9 East Asian countries or regions of the Asia-Pacific Economic Cooperation (APEC) – Japan, Singapore, Hong Kong, Thailand, South Korea, Chinese Taipei, Philippine, China, and Indonesia. All stock indexes are extracted from the Morgan Stanley Capital International (MSCI) indexes. All series for these indexes are obtained from Bloomberg. We have a sample of 4120 daily observations from January 4, 2000 to October 28, 2016. Table 3.1 presents the statistical properties for oil, gold and East Asian stock series. We find positive average oil, gold and stock returns and the obtained means are very close to zero. The oil index exhibit higher volatility than other returns. All returns distributions seem against normal as measured by the skewness and kurtosis statistics. More precisely, all returns exhibit negative skewness expect Philippine.

Insert Table 3.1 here

Table 3.2 shows the pairwise return correlations for all pairs of returns in our sample. We find a positive relationship between oil and East Asian stock markets with maximum values of 0.129 for Singapore stock markets followed by Thailand, China, and Hong Kong. Philippine stock returns exhibit the lowest correlation (0.047) with oil price. The relationship of East Asian stock related with gold exhibit weaker than those with oil with maximum values of 0.082 for Chinese stock market and minimum values of 0.041 for Thailand.

Insert Table 3.2 here

Fig. 3.1 plots the oil, gold and stock markets prices and returns. In Fig. 3.1, we graph the time series plots of oil, gold and East Asian stock prices and returns in our sample periods. We find that the oil prices were considerably increased from 2006-2007 covering the periods of OPEC cuts and decreased during the 2008 global financial crisis. The East

Asian stock prices have decreased since the global financial collapse. The oil, gold and stock returns also show high volatility during the global financial crisis.

Insert Fig. 3.1 here

3.4 Empirical results

In this section, we decomposed the obtained standardized residuals from marginal distribution process of nine East Asian stock markets and the prices of oil and gold respectively based on wavelet series in order to analyze their interdependence in different time horizon. Our application is firstly based on an AR-GARCH process for marginal distribution. Second, the obtained standardized residuals for each variable are decomposed up to 6 levels, covering the short-term, midterm, and long-term horizons. Finally, we employ the conditional copula functions to capture the interdependence between assets over different time scales.

Table 3.3 summarizes our marginal distribution results. The volatility model is used from the GARCH family, namely, GJR-GARCH (1, 1, 1). In order to satisfying the conditions of the GARCH parameters $\alpha > 0, \alpha + \beta < 1$, GARCH (1, 1) model is used for Gold and Hong Kong stock markets. All the estimated parameters are significant and different zero and the results of LB test supports the adoption of our marginal distribution specification.

Insert Table 3.3 here

Second, we decompose the obtained standardized residuals up to 6 levels based on the wavelet analysis-D1 to D6. D1 (2 days) and D2 (4 days) are high frequency fluctuations, representing the prices of oil, gold and stock markets fluctuated in the short-term horizon. D3 (8 days) and D4 (16 days) represent the fluctuations occurring in two weeks and 1 month or in the midterm horizon. D5 (32 days) and D6 (64 days) represent the long term horizon in our study. Fig. 3.2 shows the wavelet decompositions of oil, gold and East Asian stock markets from D1 to D6 in our sample periods.

Insert Fig. 3.2 here

Our third aim is to capture the joint distribution between stock indexes returns and the prices of oil and gold across the different time horizons. We choose the five constant conditional copula functions to analyze the interdependence of pairs and their tail dependence, including Normal copula, Clayton copula, Rotated Gumbel copula, Student's t copula and SJC copula. The results are reported in Table 3.4-3.10. Table 3.4 shows the estimated parameters of five constant copula specifications of the original series. From Table 3.4 we see that the interdependence between both the oil-stock pairs and the gold-stock pairs are positive and gold-stock correlation is weaker than those of oil-stock pairs. The strongest interdependence between oil and stock occurred in Singapore, followed by Thailand while that of gold-stock pairs are strongest in China, followed by Indonesia, which are consistent with the results of Table 3.2. The best copula model is the SJC copula which allows both lower tail dependence and upper tail dependence, followed by the student's t copula for most East Asian countries. According to the SJC copula estimates, we find that the lower tail dependence is weak and the upper tail dependence is close to zero for both oil-stock and gold-stock pairs. Table 3.5 presents the estimated parameters in the D1 (2 days) time scales. We find that the interdependence between both pairs (both oil-stock pairs and gold-stock pairs) are very weak even null in the 2 days high frequencies. Philippine even presents the minus relationship with oil. The best copula is the student's t copula, followed by SJC copula. Similar to the results of original series, both lower and upper tail dependence is very weak in the 2 days short-term horizon. Table 3.6 shows the constant copula estimations in the 4 days (one week) time scales. We can see that values of estimated parameters of oil-stock pairs of D2 are bigger than those of D1, meaning that the oil-stock interdependence increased in the one week time scales with the maximum value of 0.158 for Singapore and minimum value of 0.091 for Philippine while the gold and stock interdependence almost unchanged. The best copula is still the student's t copula. Similarly, we find that most lower and upper tail dependence of oil-stock pairs sharply increased in the 4 days short-term horizon while those of gold-stock pairs have no obvious growth. Table 3.7 and 3.8 present the estimated results in the 8 and 16 days time scales. We find that there are small up or down changes in the interdependence compared with those of the last time scale and the interdependence between most East Asian countries and oil markets are bigger than those of gold markets. The best copula is still the student's t copula, followed by the SJC copula. From SJC copula, most upper and lower tail dependence of oil and stock pairs increased while the gold-stock tail dependence is still very weak and close to zero in the D3 and D4 mid-term horizons.

Table 3.9 presents the empirical results in the D5 (32 days) long-term horizon. We find that most interdependence increased in this time scales. The best copula is still the student's t copula, followed by the SJC copula. From SJC copula, the lower and upper tail dependence increased sharply compared with D4. Especially the gold-stock interdependence is very weak even minus while their tail dependence is far larger than zero. Table 3.10 presents the empirical results of conditional constant copula functions in the D6 (64 days) long-term horizon. Similar with the results in Table 3.9, most interdependence increased in this time scales. The best copula is SJC copula, followed by student's t copula. From SJC copula we see that the lower and upper tail dependence increased sharply and became very strong in the long-term horizon.

Insert Table 3.4 to 3.6 here

In order to make it easier to compare, we plot the constant copula estimates from D1 to D6 for East Asian stock markets respectively in Fig. 3.3. The red lines denote the interdependence and tail dependences between oil and stock while the blue is those of gold and stock. We find that both interdependence and tail dependence between oil and stock markets are larger than those of gold and stock. The degree of the interdependence and tail dependence increased across the time scales.

Insert Fig. 3.3 here

3.5 Conclusion

This paper investigates the interdependence between East Asian stock markets and the prices of oil and gold across different time scales using the wavelet transform analysis and conditional copula functions. Specifically, we first estimate the marginal distribution respectively by using the AR-GARCH type model and then we decompose the estimated standardized residuals into time series with different horizons. Finally, we capture their joint distribution using conditional copula functions to analyse the interdependence between oil-stock pairs and gold-stock pairs across different time horizon (short-term, midterm and long-term).

We summarize our results as follows: Most interdependence between oil and East Asian stock markets is positive and weak in the original series and it varies and increases as time scales increase. The gold and East Asian stock interdependence is always weaker than those of oil-stock pairs. Similar with the interdependence estimates, we find that the tail dependence did not obviously increase in the short-term and midterm horizon and sharply increased in the long-term horizon.

Generally, empirical results provide strong evidence that interdependence between East Asian stock markets and the prices of oil and gold varies across different horizons. Our empirical results have implications for heterogeneous investors and market participants. For short-term investors, relatively low strength of interdependence and lower tail dependence between East Asian stock markets and the prices of oil and gold means that crude oil or gold is good choices to diversify risk. For long-term investor, the high strength of interdependence reduces the diversification benefit of oil, gold and stock portfolios.

Table 3.1

Descriptive statistics for oil, gold and East Asian stock markets.

	Mean	Median	Max	Min	Std.dev.	Skewness	Kurtosis
Oil	0.0001	0.0003	0.0775	-0.0719	0.0109	-0.0434	7.0412
Gold	0.0002	0.0002	0.0297	-0.0417	0.0050	-0.2729	8.0561
Japan	0.0000	0.0000	0.0567	-0.0453	0.0063	-0.3540	9.2208
Singapore	0.0001	0.0001	0.0363	-0.0427	0.0054	-0.1341	8.637
Hong Kong	0.0001	0.0000	0.0454	-0.0539	0.0060	-0.316	10.130
Thailand	0.0002	0.0000	0.0497	-0.0785	0.0070	-0.4626	11.7131
South Korea	0.0001	0.0000	0.0509	-0.0657	0.0074	-0.3795	9.3222
Chinese Taipei	0.0001	0.0000	0.0320	-0.0448	0.0066	-0.1136	6.2383
Philippine	0.0001	0.0000	0.0707	-0.0594	0.0062	0.3503	15.6174
China	0.0001	0.0000	0.0610	-0.0744	0.0081	-0.1059	9.5531
Indonesia	0.0002	0.0001	0.0440	-0.0706	0.0075	-0.4683	9.6853

Table 3.2

Pearson correlation between pairs of oil, gold and East Asian stock returns.

	WTI	Gold	Japan	Singapore	Hong Kong	Thailand	South Korea	Chinese Taipei	Philippine	China	Indonesia
WTI	1										
Gold	0.144	1									
Japan	0.086	0.045	1								
Singapore	0.129	0.048	0.493	1							
Hong Kong	0.114	0.057	0.533	0.673	1						
Thailand	0.125	0.041	0.346	0.477	0.465	1					
South Korea	0.101	0.054	0.545	0.540	0.574	0.389	1				
Chinese Taipei	0.084	0.049	0.439	0.480	0.491	0.351	0.556	1			
Philippine	0.047	0.051	0.352	0.304	0.342	0.306	0.302	0.311	1		
China	0.122	0.082	0.514	0.623	0.811	0.451	0.539	0.474	0.342	1	
Indonesia	0.095	0.077	0.346	0.468	0.433	0.380	0.355	0.366	0.350	0.440	1

Table 3.3

Parameter estimates of marginal distribution from AR (p)-GARCH (1, 1) or GJR-GARCH (1, 1, 1) with skew-t distributions.

	WTI	Gold	Japan	Singapore	Hong Kong	Thailand	South Korea	Chinese Taipei	Philippine	China	Indonesia
Mean equation											
μ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	-0.041	-0.014	0.032	-0.000	0.030	0.055	-0.004	0.020	0.085	0.043	0.049
	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)
ϕ_2	-	-	-	-	-	0.016	-	-0.012	-	-	-
						(0.016)		(0.015)			
ϕ_3	-	-	-	-	-	-		0.005	-	-	-
								(0.015)			
ϕ_4	-	-	-	-	-	-	-	-0.041	-	-	-
								(0.015)			
Variance equation											
ω	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α	0.023	0.047	0.021	0.030	0.059	0.061	0.014	0.011	0.072	0.029	0.055
	(0.004)	(0.004)	(0.009)	(0.000)	(0.005)	(0.019)	(0.004)	(0.009)	(0.015)	(0.003)	(0.019)
β	0.953	0.944	0.890	0.926	0.936	0.868	0.943	0.954	0.824	0.922	0.870
	(0.007)	(0.003)	(0.015)	(0.006)	(0.004)	(0.029)	(0.004)	(0.009)	(0.017)	(0.008)	(0.032)
γ	0.041	-	0.124	0.080	-	0.098	0.075	0.061	0.104	0.076	0.096
	(0.009)		(0.022)	(0.011)		(0.030)	(0.010)	(0.011)	(0.023)	(0.009)	(0.031)
Distribution equation											
λ	0.924	0.988	0.929	0.930	0.972	1.034	0.931	0.971	0.977	0.979	0.965
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.018)	(0.022)	(0.020)	(0.020)	(0.019)

η	8.256	5.090	8.651	8.238	6.408	6.031	6.521	6.279	5.248	6.816	4.733
	(0.491)	(0.397)	(1.196)	(0.949)	(0.591)	(0.791)	(0.642)	(1.781)	(0.421)	(0.643)	(0.456)
Q(30)	0.791	0.462	0.973	0.074	0.851	0.068	0.682	0.754	0.161	0.190	0.449
Q^2(30)	0.138	0.971	0.768	0.136	0.076	1.000	0.545	0.080	1.000	0.184	0.952

Notes: Standard errors are in parentheses. We select the AR order p according to AIC and BIC. We use GARCH (1, 1) model for Gold and Hong Kong stock market in order to satisfying the $\alpha > 0, \alpha + \beta < 1$ conditions. Q(s) and Q^2(s) are p values of the standardized residuals and the squared standardized residuals statistics of the Ljung-Box test with null hypothesis of no autocorrelation up to order s.

Table 3.4

Constant copula parameter estimates and tail dependence of the original time series.

WTI	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	ρ	η^{-1}	τ	log $\mathcal{L}$	τ^L	τ^U	log $\mathcal{L}$
Japan	0.069	9.807	0.067	0.000	8.871	1.100	0.122	−12.302	0.069	0.010	0.519	9.535	0.002	0.000	**9.817**
	(0.015)		(0.017)			(0.012)			(0.016)	(0.002)			(0.008)	(0.000)	
Singapore	0.123	31.308	0.139	0.007	32.363	1.100	0.122	35.188	0.125	0.054	0.525	**37.274**	0.034	0.001	36.671
	(0.015)		(0.019)			(0.012)			(0.016)	(0.019)			(0.017)	(0.001)	
Hong	0.098	19.824	0.109	0.000	21.935	1.100	0.122	16.407	0.098	0.010	0.528	20.977	0.021	0.000	**24.117**
Kong	(0.002)		(0.018)			(0.012)			(0.016)	(0.015)			(0.016)	(0.000)	
Thailand	0.117	28.517	0.125	0.004	26.720	1.100	0.122	23.572	0.117	0.018	0.532	29.198	0.022	0.001	**30.324**
	(0.015)		(0.019)			(0.012)			(0.016)	(0.009)			(0.015)	(0.001)	
South	0.115	27.293	0.120	0.003	24.742	1.100	0.122	22.709	0.115	0.026	0.530	28.597	0.020	0.001	**29.012**
Korea	(0.015)		(0.019)			(0.012)			(0.016)	(0.009)			(0.015)	(0.001)	
Chinese	0.076	11.980	0.093	0.001	**16.262**	1.100	0.122	0.640	0.076	0.010	0.521	12.707	0.012	0.000	15.404
Taipei	(0.015)		(0.018)			(0.012)			(0.016)	(0.016)			(0.029)	(0.000)	
Philippine	0.036	2.623	0.045	0.000	**4.176**	1.100	0.122	-27.772	0.035	0.010	0.508	3.630	0.000	0.000	3.474
	(0.016)		(0.017)			(0.012)			(0.016)	(0.000)			(0.000)	(0.000)	
China	0.112	25.884	0.130	0.005	29.088	1.100	0.122	28.847	0.112	0.030	0.527	27.916	0.035	0.000	**31.686**
	(0.015)		(0.019)			(0.012)			(0.016)	(0.016)			(0.018)	(0.000)	
Indonesia	0.092	17.502	0.092	0.001	14.794	1.100	0.122	3.066	0.092	0.010	0.527	18.103	0.004	0.002	**18.329**
	(0.015)		(0.018)			(0.012)			(0.016)	(0.004)			(0.006)	(0.004)	
Gold	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	ρ	η^{-1}	τ	log $\mathcal{L}$	τ^L	τ^U	log $\mathcal{L}$
Japan	0.030	1.890	0.042	0.000	3.647	1.100	0.122	-22.944	0.031	0.010	0.507	**4.050**	0.000	0.000	2.904

	(0.016)		(0.016)			(0.012)			(0.016)	(0.000)			(0.000)	(0.000)	
Singapore	0.055	6.263	0.063	0.000	7.808	1.100	0.122	-3.654	0.059	0.104	0.490	**26.036**	0.001	0.000	11.267
	(0.016)		(0.017)			(0.012)			(0.017)	(0.018)			(0.004)	(0.001)	
Hong	0.061	7.715	0.069	0.000	9.487	1.100	0.122	-4.792	0.062	0.010	0.517	10.674	0.003	0.000	**11.565**
Kong	(0.016)		(0.017)			(0.012)			(0.016)	(0.003)			(0.010)	(0.000)	
Thailand	0.062	7.782	0.065	0.000	7.910	1.100	0.122	-8.527	0.062	0.010	0.517	9.579	0.002	0.000	**10.276**
	(0.016)		(0.018)			(0.012)			(0.016)	(0.002)			(0.003)	(0.000)	
South	0.068	9.439	0.079	0.000	11.335	1.100	0.122	-1.699	0.069	0.010	0.519	11.944	0.005	0.000	**12.388**
Korea	(0.015)		(0.018)			(0.012)			(0.016)	(0.041)			(0.021)	(0.000)	
Chinese	0.059	7.227	0.065	0.000	8.226	1.100	0.122	-12.117	0.059	0.010	0.516	8.074	0.002	0.000	**8.880**
Taipei	(0.016)		(0.017)			(0.012)			(0.016)	(0.003)			(0.007)	(0.000)	
Philippine	0.058	6.864	0.069	0.000	8.746	1.100	0.122	-12.071	0.058	0.010	0.516	7.631	0.003	0.000	**8.733**
	(0.016)		(0.018)			(0.012)			(0.016)	(0.004)			(0.005)	(0.000)	
China	0.099	20.118	0.106	0.002	20.262	1.100	0.122	16.360	0.097	0.071	0.512	**29.545**	0.011	0.002	25.339
	(0.015)		(0.018)			(0.012)			(0.016)	(0.018)			(0.012)	(0.003)	
Indonesia	0.086	15.330	0.094	0.001	15.994	1.100	0.122	9.121	0.087	0.010	0.525	17.958	0.007	0.001	**19.933**
	(0.015)		(0.018)			(0.012)			(0.016)	(0.003)			(0.010)	(0.002)	

Notes: Bootstrapped standardized errors are reported in parentheses.

Table 3.5

Constant copula parameter estimates and tail dependence in the D1 (2 days) time scale.

WTI	Normal		Clayton			Rotated Gumbel			Student's t				SJC		
	ρ	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	ρ	η^{-1}	τ	log $\mathcal{L}$	τ^L	τ^U	log $\mathcal{L}$
Japan	0.008	0.129	0.015	0.000	0.195	1.100	0.122	-19.472	0.006	0.166	0.457	**8.438**	0.000	0.000	0.196
	(0.020)		(0.021)			(0.014)			(0.019)	(0.035)			(0.000)	(0.000)	
Singapore	0.078	12.620	0.139	0.007	14.779	1.100	0.122	19.646	0.097	0.196	0.480	**27.504**	0.037	0.002	18.290
	(0.019)		(0.027)			(0.014)			(0.019)	(0.033)			(0.026)	(0.005)	
Hong	0.050	5.153	0.089	0.000	6.575	1.100	0.122	5.741	0.063	0.205	0.466	**21.455**	0.020	0.000	8.479
Kong	(0.019)		(0.026)			(0.014)			(0.019)	(0.032)			(0.019)	(0.000)	
Thailand	0.065	8.701	0.117	0.003	11.700	1.100	0.122	12.874	0.072	0.187	0.474	**20.861**	0.039	0.000	13.924
	(0.019)		(0.026)			(0.014)			(0.019)	(0.034)			(0.021)	(0.000)	
South	0.057	6.608	0.100	0.001	8.244	1.100	0.122	9.002	0.068	0.188	0.472	**18.521**	0.024	0.000	10.434
Korea	(0.019)		(0.026)			(0.014)			(0.019)	(0.034)			(0.020)	(0.000)	
Chinese	0.025	1.320	0.053	0.000	2.504	1.100	0.122	-9.488	0.028	0.153	0.467	**8.467**	0.001	0.000	2.549
Taipei	(0.019)		(0.025)			(0.014)			(0.019)	(0.035)			(0.002)	(0.000)	
Philippine	-0.033	2.262	0.000	0.000	-0.005	1.100	0.122	-38.883	-0.044	0.147	0.445	**10.581**	0.000	0.000	-5.019
	(0.019)		(0.000)			(0.014)			(0.019)	(0.033)			(0.000)	(0.000)	
China	0.039	3.160	0.076	0.000	4.892	1.100	0.122	-0.173	0.048	0.196	0.463	**17.577**	0.010	0.000	5.5719
	(0.019)		(0.025)			(0.014)			(0.019)	(0.033)			(0.017)	(0.000)	
Indonesia	0.038	2.998	0.066	0.000	4.028	1.100	0.122	-5.485	0.043	0.114	0.482	**7.358**	0.004	0.000	4.615
	(0.019)		(0.024)			(0.014)			(0.019)	(0.036)			(0.011)	(0.000)	
Gold	Normal		Clayton			Rotated Gumbel			Student's t				SJC		
	ρ	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	ρ	η^{-1}	τ	log $\mathcal{L}$	τ^L	τ^U	log $\mathcal{L}$
Japan	0.062	7.790	0.102	0.001	8.134	1.100	0.122	9.202	0.078	0.219	0.468	**27.054**	0.000	0.034	12.183
	(0.019)		(0.026)			(0.014)			(0.019)	(0.032)			(0.000)	(0.021)	

Singapore	0.054	6.053	0.089	0.000	6.176	1.100	0.122	8.591	0.002	0.295	0.447	**44.234**	0.000	0.045	13.437
	(0.019)		(0.027)			(0.014)			(0.019)	(0.030)			(0.000)	(0.022)	
Hong	0.057	6.734	0.099	0.001	7.739	1.100	0.122	9.307	0.069	0.256	0.456	**35.363**	0.000	0.033	11.699
Kong	(0.019)		(0.026)			(0.014)			(0.019)	(0.031)			(0.000)	(0.020)	
Thailand	0.032	2.103	0.057	0.000	2.750	1.100	0.122	-4.539	0.041	0.209	0.458	**19.897**	0.000	0.002	4.004
	(0.019)		(0.025)			(0.014)			(0.019)	(0.032)			(0.000)	(0.007)	
South	0.070	10.601	0.115	0.002	10.256	1.100	0.122	12.577	0.090	0.193	0.478	**26.003**	0.000	0.027	14.165
Korea	(0.019)		(0.026)			(0.014)			(0.019)	(0.032)			(0.002)	(0.023)	
Chinese	0.053	5.702	0.079	0.000	4.954	1.100	0.122	0.946	0.065	0.104	0.492	**9.168**	0.000	0.015	7.630
Taipei	(0.019)		(0.026)			(0.014)			(0.019)	(0.038)			(0.000)	(0.017)	
Philippine	0.041	3.531	0.062	0.000	3.397	1.100	0.122	-5.864	0.049	0.117	0.484	**8.262**	0.000	0.005	5.102
	(0.019)		(0.025)			(0.014)			(0.019)	(0.036)			(0.000)	(0.013)	
China	0.086	15.365	0.136	0.006	14.604	1.100	0.122	19.524	0.100	0.217	0.476	**35.206**	0.000	0.061	23.043
	(0.019)		(0.026)			(0.014)			(0.019)	(0.032)			(0.000)	(0.023)	
Indonesia	0.061	7.642	0.090	0.000	7.096	1.100	0.122	5.949	0.068	0.180	0.474	**22.151**	0.000	0.034	12.885
	(0.019)		(0.025)			(0.014)			(0.019)	(0.031)			(0.000)	(0.020)	

Notes: Bootstrapped standardized errors are reported in parentheses.

Table 3.6

Constant copula parameter estimates and tail dependence in the D2 (4 days) time scale.

WTI	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	ρ	η^{-1}	τ	log $\mathcal{L}$	τ^L	τ^U	log $\mathcal{L}$
Japan	0.111	25.350	0.185	0.023	26.195	1.100	0.122	31.603	0.122	0.204	0.486	**37.583**	0.026	0.049	34.121
	(0.019)		(0.027)			(0.013)			(0.019)	(0.036)			(0.026)	(0.029)	
Singapore	0.158	52.080	0.277	0.082	56.425	1.147	0.170	65.855	0.178	0.240	0.498	**72.969**	0.096	0.066	68.752
	(0.019)		(0.027)			(0.014)			(0.018)	(0.034)			(0.029)	(0.029)	
Hong Kong	0.135	37.939	0.219	0.043	35.983	1.119	0.142	44.699	0.153	0.186	0.501	49.248	0.040	0.073	**49.404**
	(0.019)		(0.027)			(0.014)			(0.018)	(0.036)			(0.026)	(0.029)	
Thailand	0.128	33.874	0.210	0.037	32.965	1.114	0.137	39.994	0.146	0.203	0.495	**47.196**	0.028	0.078	45.050
	(0.019)		(0.027)			(0.014)			(0.018)	(0.035)			(0.024)	(0.029)	
South Korea	0.148	45.477	0.234	0.052	40.391	1.131	0.154	51.723	0.107	0.220	0.493	**65.776**	0.023	0.121	62.106
	(0.019)		(0.027)			(0.014)			(0.018)	(0.034)			(0.019)	(0.026)	
Chinese Taipei	0.094	18.353	0.163	0.014	20.589	1.100	0.122	25.957	0.107	0.220	0.478	**33.284**	0.032	0.019	25.366
	(0.019)		(0.026)			(0.014)			(0.019)	(0.035)			(0.030)	(0.025)	
Philippine	0.091	16.918	0.133	0.006	13.767	1.100	0.122	18.732	0.106	0.156	0.493	**25.014**	0.000	0.066	23.512
	(0.019)		(0.026)			(0.014)			(0.019)	(0.036)			(0.000)	(0.022)	
China	0.155	50.066	0.257	0.067	48.171	1.139	0.162	59.365	0.174	0.217	0.501	66.303	0.059	0.098	**66.539**
	(0.019)		(0.027)			(0.014)			(0.018)	(0.035)			(0.028)	(0.028)	
Indonesia	0.128	33.870	0.211	0.037	33.926	1.113	0.136	40.499	0.149	0.170	0.504	**44.015**	0.043	0.054	43.154
	(0.019)		(0.027)			(0.014)			(0.018)	(0.036)			(0.028)	(0.029)	
Gold	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	κ	τ^L	log $\mathcal{L}$	ρ	η^{-1}	τ	log $\mathcal{L}$	τ^L	τ^U	log $\mathcal{L}$
Japan	0.020	0.787	0.048	0.000	1.954	1.100	0.122	-8.890	0.020	0.255	0.439	**22.492**	0.000	0.000	2.018
	(0.020)		(0.025)			(0.014)			(0.019)	(0.033)			(0.000)	(0.000)	

Singapore	0.062	8.451	0.112	0.002	9.918	1.100	0.122	15.700	0.066	0.320	0.440	**45.260**	0.000	0.048	14.730
	(0.019)		(0.026)			(0.014)			(0.019)	(0.031)			(0.000)	(0.022)	
Hong	0.059	7.095	0.098	0.001	7.871	1.100	0.122	8.962	0.059	0.263	0.451	**29.736**	0.000	0.037	12.438
Kong	(0.019)		(0.026)			(0.014)			(0.019)	(0.033)			(0.000)	(0.021)	
Thailand	0.088	15.871	0.153	0.011	17.695	1.100	0.122	22.698	0.103	0.215	0.477	**29.464**	0.028	0.014	22.010
	(0.019)		(0.027)			(0.014)			(0.019)	(0.035)			(0.030)	(0.023)	
South	0.067	9.223	0.117	0.003	10.678	1.100	0.122	12.533	0.079	0.239	0.463	**28.072**	0.000	0.033	13.647
Korea	(0.019)		(0.027)			(0.014)			(0.019)	(0.034)			(0.001)	(0.029)	
Chinese	0.065	8.653	0.125	0.004	12.711	1.100	0.122	13.715	0.072	0.233	0.462	**25.577**	0.046	0.000	14.760
Taipei	(0.019)		(0.026)			(0.014)			(0.019)	(0.034)			(0.022)	(0.000)	
Philippine	0.059	7.189	0.101	0.001	8.410	1.100	0.122	8.142	0.065	0.215	0.464	**21.645**	0.015	0.000	10.698
	(0.019)		(0.026)			(0.014)			(0.019)	(0.034)			(0.022)	(0.002)	
China	0.101	20.983	0.174	0.019	22.747	1.100	0.122	30.631	0.110	0.280	0.465	**48.483**	0.022	0.050	31.196
	(0.019)		(0.027)			(0.014)			(0.019)	(0.033)			(0.025)	(0.031)	
Indonesia	0.073	10.885	0.131	0.005	14.186	1.100	0.122	16.090	0.079	0.212	0.470	**24.536**	0.046	0.000	16.558
	(0.019)		(0.026)			(0.014)			(0.019)	(0.035)			(0.022)	(0.000)	

Notes: Bootstrapped standardized errors are reported in parentheses.

Table 3.7

Constant copula parameter estimates and tail dependence in the D3 (8 days) time scale.

WTI	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$
Japan	0.142	41.630	0.252	0.064	42.157	1.138	0.162	54.808	0.157	0.363	0.463	**86.714**	0.041	0.113	61.195
	(0.019)		(0.028)			(0.014)			(0.018)	(0.032)			(0.028)	(0.030)	
Singapore	0.143	42.360	0.257	0.067	45.899	1.140	0.163	59.061	0.147	0.391	0.453	**97.904**	0.062	0.101	64.666
	(0.019)		(0.028)			(0.014)			(0.018)	(0.031)			(0.030)	(0.030)	
Hong	0.110	24.879	0.203	0.033	28.294	1.113	0.136	38.435	0.123	0.378	0.448	**73.326**	0.034	0.067	38.930
Kong	(0.019)		(0.028)			(0.014)			(0.018)	(0.032)			(0.031)	(0.033)	
Thailand	0.162	54.979	0.292	0.093	58.861	1.157	0.180	71.613	0.181	0.309	0.483	**91.652**	0.093	0.094	76.392
	(0.019)		(0.028)			(0.014)			(0.018)	(0.032)			(0.030)	(0.031)	
South	0.185	72.410	0.344	0.133	79.076	1.187	0.207	96.921	0.207	0.407	0.472	**140.545**	0.118	0.130	102.417
Korea	(0.019)		(0.028)			(0.015)			(0.018)	(0.031)			(0.031)	(0.030)	
Chinese	0.125	32.536	0.221	0.044	34.181	1.122	0.145	44.690	0.136	0.344	0.459	**72.547**	0.039	0.082	48.403
Taipei	(0.019)		(0.028)			(0.014)			(0.018)	(0.032)			(0.028)	(0.031)	
Philippine	0.092	17.390	0.160	0.013	18.356	1.100	0.122	25.308	0.102	0.281	0.461	**41.199**	0.008	0.050	25.617
	(0.019)		(0.027)			(0.014)			(0.019)	(0.034)			(0.016)	(0.031)	
China	0.175	63.891	0.338	0.128	76.385	1.177	0.198	87.819	0.199	0.350	0.481	**109.867**	0.142	0.078	90.553
	(0.019)		(0.028)			(0.015)			(0.018)	(0.032)			(0.029)	(0.031)	
Indonesia	0.139	40.083	0.251	0.063	43.369	1.136	0.159	54.487	0.161	0.301	0.478	**71.203**	0.070	0.072	56.532
	(0.019)		(0.028)			(0.014)			(0.018)	(0.033)			(0.030)	(0.031)	
Gold	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$
Japan	0.013	0.328	0.033	0.000	0.903	1.100	0.122	-11.008	-0.002	0.365	0.407	**45.783**	0.000	0.000	1.776
	(0.020)		(0.025)			(0.014)			(0.016)	(0.031)			(0.000)	(0.000)	

Singapore	0.058	7.003	0.097	0.001	7.500	1.100	0.122	9.394	0.051	0.343	0.430	**44.543**	0.000	0.059	15.349
	(0.019)		(0.026)			(0.014)			(0.019)	(0.032)			(0.000)	(0.022)	
Hong	0.020	0.806	0.033	0.000	0.889	1.100	0.122	-8.421	0.018	0.346	0.418	**37.420**	0.000	0.005	3.636
Kong	(0.019)		(0.025)			(0.014)			(0.019)	(0.033)			(0.000)	(0.041)	
Thailand	0.084	14.541	0.160	0.013	19.246	1.100	0.122	24.768	0.095	0.295	0.456	**42.508**	0.074	0.000	22.996
	(0.019)		(0.027)			(0.014)			(0.018)	(0.033)			(0.023)	(0.000)	
South	0.078	12.469	0.138	0.007	14.286	1.100	0.122	20.630	0.080	0.338	0.441	**49.371**	0.000	0.064	20.911
Korea	(0.019)		(0.027)			(0.014)			(0.019)	(0.033)			(0.000)	(0.024)	
Chinese	0.082	13.873	0.146	0.009	16.077	1.100	0.122	21.956	0.094	0.248	0.467	**31.611**	0.042	0.002	20.162
Taipei	(0.019)		(0.027)			(0.014)			(0.019)	(0.035)			(0.030)	(0.008)	
Philippine	0.080	13.061	0.134	0.006	14.235	1.100	0.122	20.825	0.078	0.311	0.446	**44.043**	0.000	0.062	21.449
	(0.019)		(0.026)			(0.013)			(0.019)	(0.033)			(0.000)	(0.023)	
China	0.112	26.111	0.208	0.036	31.264	1.115	0.138	41.907	0.115	0.384	0.444	**77.971**	0.054	0.051	41.663
	(0.019)		(0.028)			(0.014)			(0.018)	(0.032)			(0.031)	(0.031)	
Indonesia	0.112	26.076	0.195	0.029	27.823	1.110	0.132	38.755	0.123	0.303	0.464	**59.263**	0.035	0.060	39.183
	(0.019)		(0.027)			(0.014)			(0.018)	(0.032)			(0.028)	(0.031)	

Notes: Bootstrapped standardized errors are reported in parentheses.

Table 3.8

Constant copula parameter estimates and tail dependence in the D4 (16 days) time scale.

WTI	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$
Japan	0.085	14.810	0.243	0.057	25.222	1.132	0.155	37.146	0.113	0.476	0.424	**101.172**	0.080	0.080	37.787
	(0.025)		(0.033)			(0.016)			(0.020)	(0.032)			(0.037)	(0.037)	
Singapore	0.187	73.353	0.449	0.213	93.607	1.240	0.251	113.259	0.231	0.467	0.469	**169.840**	0.177	0.203	130.424
	(0.024)		(0.032)			(0.018)			(0.032)	(0.029)			(0.032)	(0.029)	
Hong	0.176	64.843	0.479	0.235	102.939	1.247	0.257	115.269	0.210	0.476	0.460	**170.267**	0.232	0.151	127.426
Kong	(0.026)		(0.033)			(0.018)			(0.020)	(0.033)			(0.027)	(0.034)	
Thailand	0.188	74.031	0.459	0.221	95.431	1.242	0.253	110.251	0.230	0.416	0.479	**151.023**	0.180	0.209	131.215
	(0.025)		(0.032)			(0.018)			(0.020)	(0.033)			(0.031)	(0.029)	
South	0.159	52.904	0.440	0.207	83.290	1.229	0.242	97.195	0.201	0.468	0.458	**143.103**	0.208	0.142	106.582
Korea	(0.026)		(0.033)			(0.018)			(0.020)	(0.033)			(0.029)	(0.035)	
Chinese	0.162	54.349	0.410	0.185	75.459	1.219	0.234	93.992	0.205	0.476	0.458	**166.907**	0.160	0.186	108.463
Taipei	(0.025)		(0.033)			(0.018)			(0.020)	(0.033)			(0.032)	(0.030)	
Philippine	0.138	39.411	0.365	0.149	56.712	1.190	0.210	68.025	0.180	0.402	0.463	**104.392**	0.136	0.150	78.815
	(0.026)		(0.033)			(0.018)			(0.021)	(0.034)			(0.033)	(0.033)	
China	0.212	95.053	0.576	0.294	142.574	1.296	0.293	156.087	0.260	0.476	0.479	**204.082**	0.280	0.180	171.932
	(0.025)		(0.033)			(0.019)			(0.020)	(0.034)			(0.024)	(0.035)	
Indonesia	0.142	41.907	0.369	0.153	58.277	1.195	0.214	71.055	0.181	0.456	0453	**124.212**	0.121	0.184	87.633
	(0.026)		(0.033)			(0.018)			(0.020)	(0.033)			(0.035)	(0.029)	
Gold	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$

Japan	-0.038	2.936	0.000	0.000	-0.005	1.100	0.122	-20.008	-0.051	0.426	0.377	**59.631**	0.000	0.000	-3.073
	(0.025)		(0.000)			(0.016)			(0.020)	(0.034)			(0.000)	(0.000)	
Singapore	0.014	0.409	0.052	0.000	1.157	1.100	0.122	1.988	0.001	0.476	0.384	**101.572**	0.000	0.065	10.085
	(0.024)		(0.035)			(0.016)			(0.009)	(0.032)			(0.000)	(0.028)	
Hong	0.071	10.275	0.224	0.045	20.716	1.119	0.142	30.196	0.072	0.476	0.409	**98.752**	0.070	0.075	32.210
Kong	(0.026)		(0.034)			(0.016)			(0.020)	(0.033)			(0.036)	(0.036)	
Thailand	0.057	6.644	0.198	0.030	15.719	1.115	0.138	28.218	0.087	0.476	0.414	**132.415**	0.060	0.067	26.154
	(0.026)		(0.035)			(0.016)			(0.021)	(0.034)			(0.039)	(0.040)	
South	0.001	0.001	0.050	0.000	0.888	1.100	0.122	2.043	-0.010	0.476	0.380	**95.338**	0.000	0.028	3.599
Korea	(0.008)		(0.038)			(0.016)			(0.020)	(0.033)			(0.000)	(0.028)	
Chinese	0.035	2.510	0.134	0.006	7.362	1.100	0.122	12.194	0.040	0.425	0.408	**60.025**	0.071	0.000	11.387
Taipei	(0.025)		(0.034)			(0.016)			(0.020)	(0.034)			(0.027)	(0.000)	
Philippine	0.061	7.585	0.232	0.050	22.710	1.119	0.142	29.857	0.077	0.476	0.411	**101.335**	0.145	0.000	29.993
	(0.026)		(0.034)			(0.016)			(0.021)	(0.033)			(0.025)	(0.000)	
China	0.074	11.491	0.254	0.065	26.214	1.133	0.156	36.838	0.087	0.476	0.415	**132.262**	0.101	0.073	38.547
	(0.026)		(0.034)			(0.016)			(0.021)	(0.035)			(0.035)	(0.037)	
Indonesia	0.142	41.651	0.386	0.166	66.095	1.200	0.218	78.707	0.171	0.476	0.445	**166.322**	0.153	0.168	93.795
	(0.026)		(0.033)			(0.017)			(0.020)	(0.033)			(0.032)	(0.031)	

Notes: Bootstrapped standardized errors are reported in parentheses.

Table 3.9

Constant copula parameter estimates and tail dependence in the D5 (32 days) time scale.

Gold	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$
Japan	0.176	64.622	1.118	0.538	266.924	1.673	0.487	325.876	0.462	0.476	0.560	**462.024**	0.477	0.507	433.488
	(0.030)		(0.044)			(0.027)			(0.040)	(0.077)			(0.020)	(0.016)	
Singapore	0.182	69.671	1.004	0.501	237.429	1.591	0.454	281.361	0.408	0.476	0.537	**414.319**	0.444	0.473	381.550
	(0.035)		(0.042)			(0.026)			(0.036)	(0.063)			(0.021)	(0.017)	
Hong	0.198	82.500	1.166	0.552	305.956	1.686	0.492	354.915	0.469	0.476	0.563	**483.978**	0.504	0.488	455.540
Kong	(0.031)		(0.044)			(0.027)			(0.046)	(0.092)			(0.016)	(0.018)	
Thailand	0.240	121.663	1.196	0.560	338.567	1.708	0.500	392.430	0.497	0.476	0.576	**516.756**	0.507	0.499	493.281
	(0.034)		(0.043)			(0.027)			(0.036)	(0.078)			(0.016)	(0.017)	
South	0.170	60.130	1.108	0.535	260.970	1.669	0.485	319.391	0.456	0.476	0.558	**460.542**	0.473	0.515	435.570
Korea	(0.030)		(0.044)			(0.027)			(0.047)	(0.088)			(0.020)	(0.015)	
Chinese	0.126	33.089	0.904	0.465	175.230	1.537	0.430	220.122	0.354	0.476	0.515	**379.584**	0405	0.468	322.343
Taipei	(0.033)		(0.043)			(0.026)			(0.037)	(0.055)			(0.025)	(0.016)	
Philippine	0.119	29.455	0.958	0.485	200.677	1.544	0.433	230.653	0.309	0.476	0.497	**367.786**	0.450	0.415	313.124
	(0.033)		(0.043)			(0.026)			(0.046)	(0.061)			(0.018)	(0.022)	
China	0.283	171.456	1.415	0.613	438.961	1.862	0.549	517.525	0.583	0.476	0.615	636.560	0.549	0.578	**650.844**
	(0.028)		(0.045)			(0.028)			(0.053)	(0.150)			(0.017)	(0.013)	
Indonesia	0.169	59.409	1.151	0.548	282.958	1.681	0.490	331.385	0.448	0.476	0.554	**447.841**	0.499	0.486	431.168
	(0.029)		(0.044)			(0.027)			(0.049)	(0.088)			(0.017)	(0.018)	
Gold	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$
Japan	-0.097	19.425	0.371	0.154	11.405	1.212	0.229	29.483	-0.246	0.476	0.299	**331.722**	0.244	0.277	70.118

	(0.033)		(0.053)			(0.027)			(0.040)	(0.047)			(0.030)	(0.026)	
Singapore	0.008	0.144	0.516	0.261	45.764	1.295	0.292	70.517	0.045	0.476	0.400	**287.141**	0.262	0.348	133.192
	(0.043)		(0.044)			(0.025)			(0.035)	(0.035)			(0.032)	(0.021)	
Hong	0.157	51.537	0.921	0.471	189.579	1.551	0.436	238.210	0.382	0.476	0.527	**387.032**	0.396	0.487	348.935
Kong	(0.035)		(0.042)			(0.026)			(0.033)	(0.053)			(0.027)	(0.015)	
Thailand	0.095	18.705	0.783	0.412	138.623	1.443	0.383	164.452	0.251	0.476	0.475	**321.560**	0.384	0.369	228.810
	(0.039)		(0.042)			(0.025)			(0.034)	(0.042)			(0.022)	(0.023)	
South	0.037	2.791	0.748	0.396	105.692	1.437	0.380	138.953	0.172	0.476	0.445	**339.646**	0.370	0.403	218.417
Korea	(0.033)		(0.044)			(0.026)			(0.042)	(0.040)			(0.024)	(0.020)	
Chinese	0.058	6.809	0.716	0.380	106.295	1.404	0.361	130.983	0.179	0.476	0.448	**303.575**	0.354	0.370	199.207
Taipei	(0.037)		(0.043)			(0.025)			(0.035)	(0.038)			(0.024)	(0.022)	
Philippine	0.087	15.591	0.853	0.444	155.175	1.484	0.405	185.061	0.279	0.476	0.486	**349.545**	0.416	0.384	253.518
	(0.036)		(0.043)			(0.026)			(0.036)	(0.045)			(0.020)	(0.024)	
China	0.160	56.990	0.991	0.497	220.705	1.584	0.451	263.123	0.384	0.476	0.527	**391.098**	0.431	0.488	375.876
	(0.032)		(0.042)			(0.026)			(0.042)	(0.068)			(0.023)	(0.015)	
Indonesia	0.065	8.778	0.811	0.425	128.057	1.472	0.399	163.997	0.221	0.476	0.464	**330.911**	0.388	0.419	249.772
	(0.032)		(0.044)			(0.026)			(0.041)	(0.043)			(0.023)	(0.019)	

Notes: Bootstrapped standardized errors are reported in parentheses.

Table 3.10

Constant copula parameter estimates and tail dependence in the D6 (64 days) time scale.

WTI	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$
Japan	0.234	116.356	2.413	0.750	818.850	2.473	0.677	973.632	0.749	0.476	0.704	1.027E03	0.703	0.718	**1.163E03**
	(0.019)		(0.056)			(0.035)			(0.008)	(0.047)			(0.010)	(0.008)	
Singapore	0.192	77.050	1.986	0.705	600.756	2.214	0.632	731.400	0.678	0.476	0.664	806.616	0.646	0.685	**934.389**
	(0.020)		(0.053)			(0.033)			(0.010)	(0.044)			(0.013)	(0.008)	
Hong	0.178	65.890	1.987	0.706	595.967	2.215	0.633	724.267	0.688	0.476	0.669	820.139	0.651	0.678	**914.787**
Kong	(0.021)		(0.053)			(0.033)			(0.011)	(0.050)			(0.012)	(0.009)	
Thailand	0.313	212.236	2.375	0.750	849.615	2.469	0.676	1.011E03	0.750	0.476	0.705	1.059E03	0.694	0.727	**1.210E03**
	(0. 018)		(0.055)			(0.035)			(0.008)	(0.047)			(0.011)	(0.007)	
South	0.285	174.298	2.502	0.758	886.425	2.539	0.686	1.053E03	0.767	0.476	0.715	1.112E03	0.709	0.737	**1.251E03**
Korea	(0.018)		(0.057)			(0.036)			(0.008)	(0.050)			(0.011)	(0.007)	
Chinese	0.250	133.026	2.311	0.741	780.405	2.405	0.666	924.373	0.729	0.476	0.692	968.947	0.691	0.705	**1.109E03**
Taipei	(0.019)		(0.055)			(0.035)			(0.009)	(0.045)			(0.010)	(0.008)	
Philippine	0.151	47.666	2.042	0.712	614.853	2.240	0.637	741.684	0.683	0.476	0.666	803.837	0.660	0.672	**917.377**
	(0.020)		(0.053)			(0.033)			(0.011)	(0.044)			(0.011)	(0.010)	
China	0.277	164.292	2.359	0.745	806.460	2.471	0.676	981.967	0.757	0.476	0.709	1.063E03	0.686	0.740	**1.203E03**
	(0.019)		(0.056)			(0.035)			(0.008)	(0.050)			(0.014)	(0.006)	
Indonesia	0.184	70.923	2.105	0.719	648.736	2.274	0.644	778.829	0.695	0.476	0.673	843.339	0.667	0.684	**967.133**
	(0.020)		(0.054)			(0.033)			(0.009)	(0.044)			(0.011)	(0.009)	
Gold	Normal		Clayton			RGumbel			Student's t				SJC		
	ρ	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	κ	τ^L	$\log \mathcal{L}$	ρ	η^{-1}	τ	$\log \mathcal{L}$	τ^L	τ^U	$\log \mathcal{L}$
Japan	-0.083	14.084	1.485	0.627	294.484	1.893	0.558	383.151	-0.665	0.476	0.155	**747.760**	0.581	0.590	553.372

	(0.021)		(0.052)			(0.031)			(0.012)	(0.047)			(0.014)	(0.013)	
Singapore	-0.013	0.346	1.410	0.612	291.095	1.837	0.542	364.778	-0.525	0.476	0.205	548.927	0.563	0.576	**531.023**
	(0.022)		(0.050)			(0.030)			(0.019)	(0.040)			(0.015)	(0.013)	
Hong	0.109	24.529	1.687	0.663	435.629	2.031	0.593	544.950	0.623	0.476	0.635	674.308	0.604	0.643	**732.013**
Kong	(0.022)		(0.051)			(0.031)			(0.015)	(0.050)			(0.015)	(0.010)	
Thailand	0.266	151.488	2.197	0.730	733.987	2.362	0.659	885.168	0.739	0.476	0.698	981.326	0.676	0.704	**1.067E03**
	(0.020)		(0.055)			(0.035)			(0.012)	(0.066)			(0.012)	(0.008)	
South	0.002	0.005	1.635	0.655	377.079	1.985	0.582	476.513	0.578	0.476	0.613	606.856	0.605	0.619	**653.795**
Korea	(0.014)		(0.052)			(0.031)			(0.015)	(0.039)			(0.013)	(0.011)	
Chinese	0.042	3.643	1.705	0.666	422.903	2.013	0.589	514.617	0.592	0.476	0.620	629.341	0.621	0.614	**684.871**
Taipei	(0.022)		(0.052)			(0.031)			(0.014)	(0.041)			(0.012)	(0.013)	
Philippine	0.058	6.842	1.723	0.669	434.115	2.043	0.596	540.313	0.614	0.476	0.630	654.222	0.615	0.630	**710.229**
	(0.021)		(0.052)			(0.032)			(0.014)	(0.044)			(0.013)	(0.011)	
China	0.160	53.429	1.942	0.700	568.651	2.183	0.626	690.898	0.675	0.476	0.662	786.564	0.646	0.672	**884.691**
	(0.021)		(0.053)			(0.033)			(0.011)	(0.046)			(0.012)	(0.009)	
Indonesia	0.182	69.363	1.927	0.698	573.287	2.166	0.623	689.517	0.655	0.476	0.652	754.665	0.640	0.664	**876.851**
	(0.021)		(0.052)			(0.032)			(0.012)	(0.043)			(0.012)	(0.010)	

Notes: Bootstrapped standardized errors are reported in parentheses.


Oil
150
100
50
0
0.1
0.05
0
−0.05
−0.1
Gold
2000
1500
1000
500
0
0.05
0
−0.05
Japan
2000
1500
1000
500
0.05
0
−0.05
Singapore
6000
5000
4000
3000
2000
1000
0.05
0
−0.05
x 10^4
Hong Kong
8
6
4
2
0
0.06
0.04
0.02
0
−0.02
−0.04
−0.06
Thailand
1000
800
600
400
200
0
0.1
0.05
0
−0.05
−0.1
South Korea
600
500
400
300
200
100
0
0.06
0.04
0.02
0
−0.02
−0.04
−0.06
Taiwan
250
200
150
100
50
0.05
0
−0.05
2000
2001
2003
2005
2007
2009
2011
2013
2015

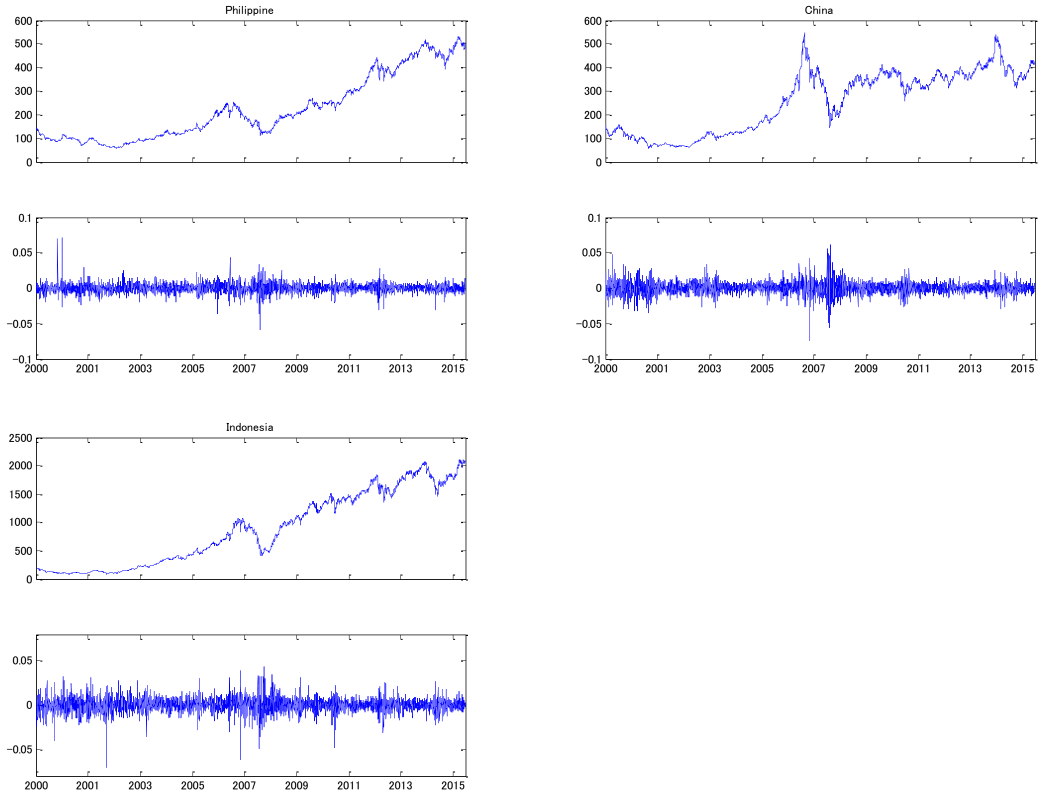
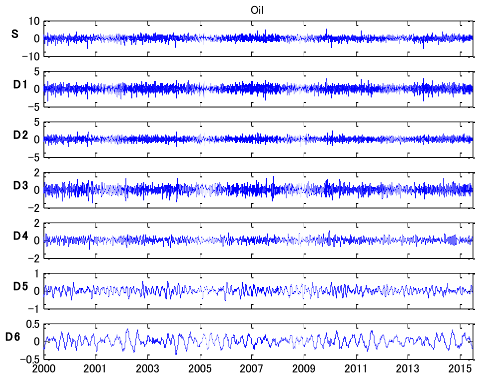
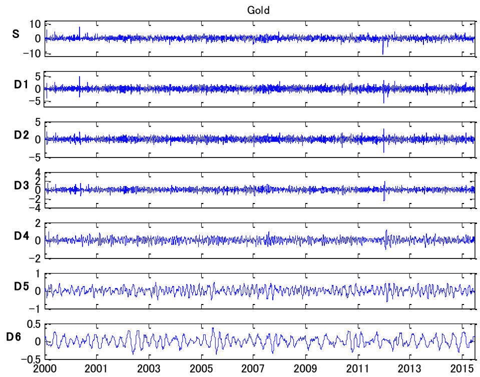
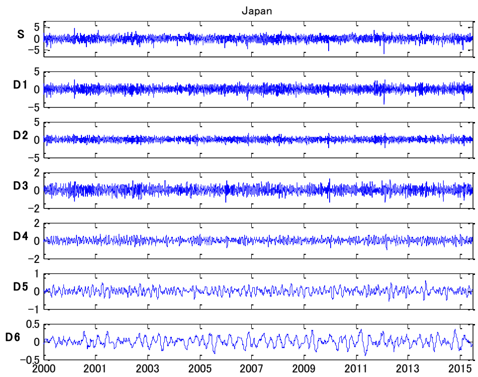
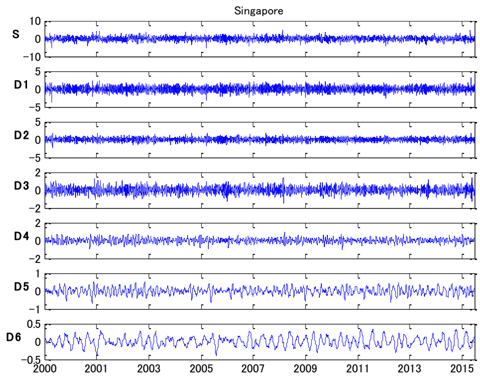


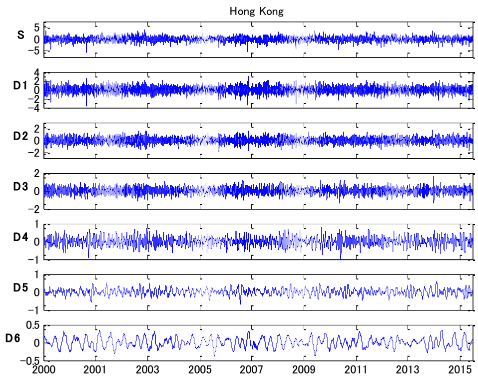
Fig. 3.1. Time series prices and returns plots.

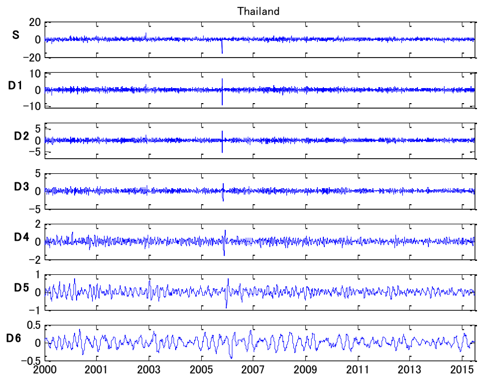

Oil
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015

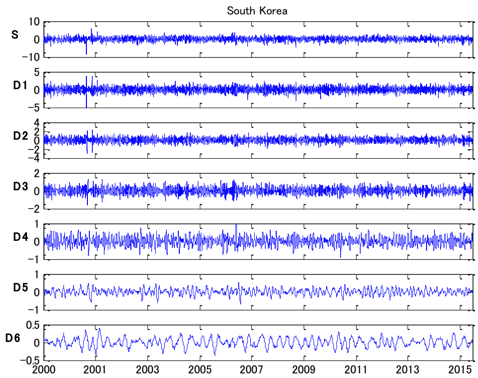

Gold
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015

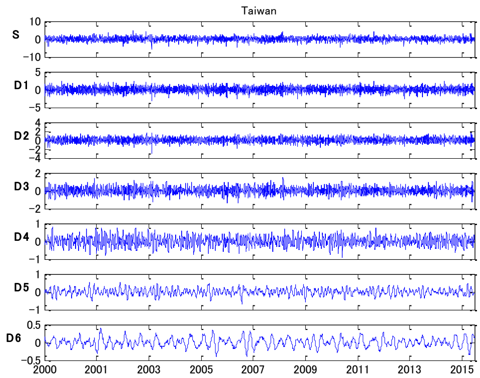

Japan
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015


Singapore
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015


Hong Kong
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015


Thailand
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015


South Korea
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015


Taiwan
S
D1
D2
D3
D4
D5
D6
2000 2001 2003 2005 2007 2009 2011 2013 2015

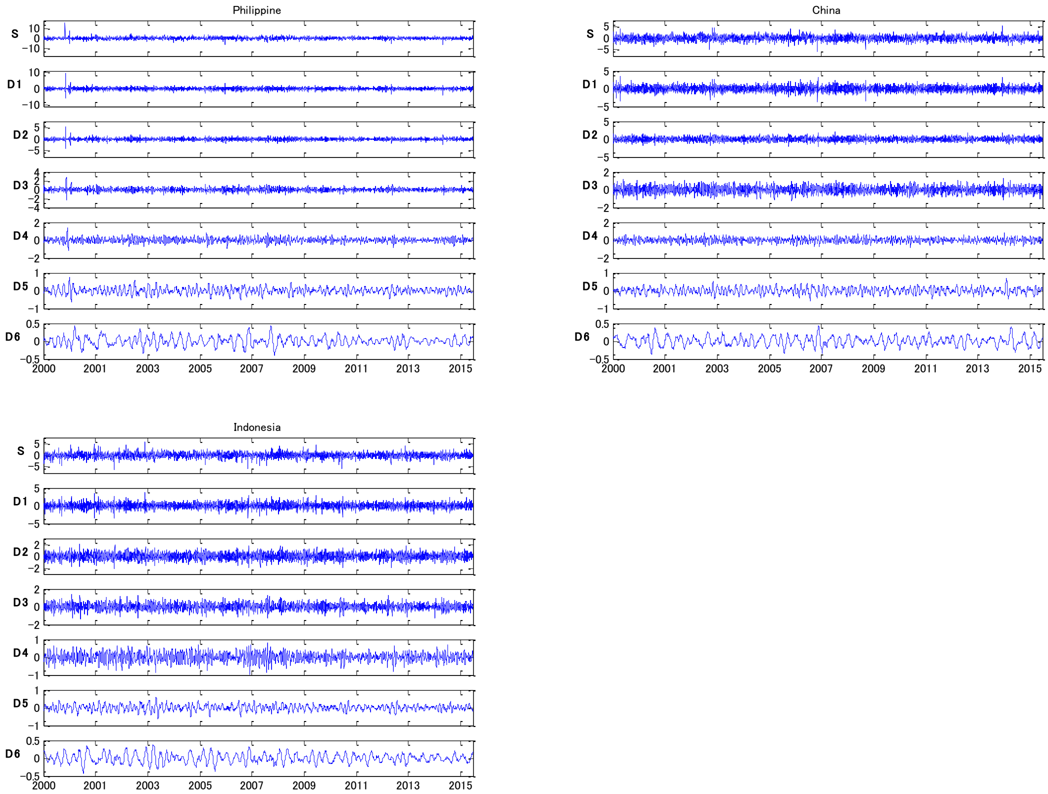
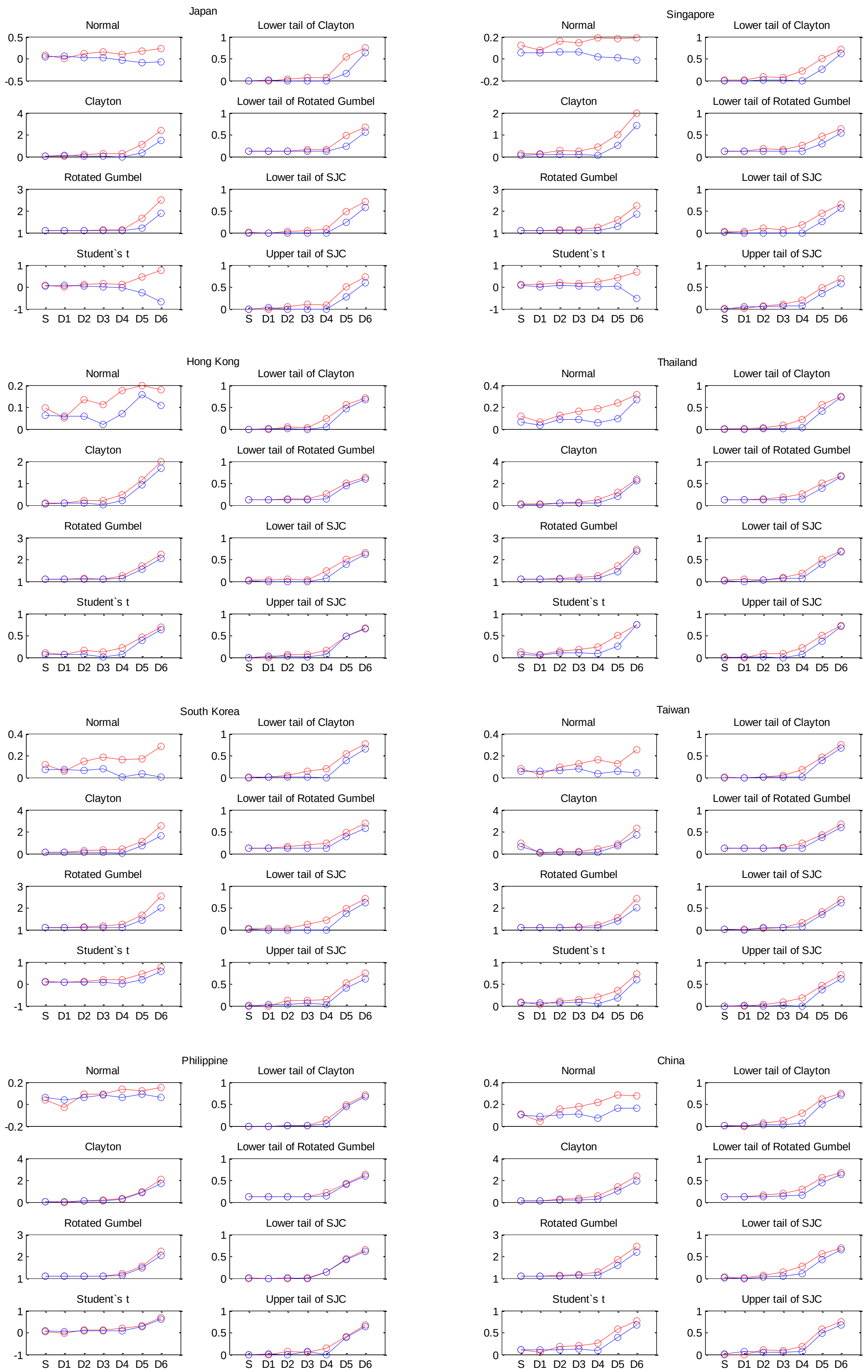


Fig. 3.2. Wavelet decomposition of standardized residual series for oil, gold and East Asian stock markets. s represents the original series.


Japan
Singapore
Hong Kong
Thailand
South Korea
Taiwan
Philippine
China
Normal
Lower tail of Clayton
Clayton
Lower tail of Rotated Gumbel
Rotated Gumbel
Lower tail of SJC
Student`s t
Upper tail of SJC
S D1 D2 D3 D4 D5 D6

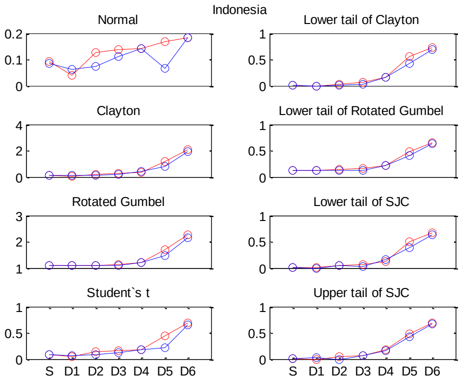


Fig. 3.3. Constant copula estimates and tail dependence. Red (Blue) lines represent the results of oil-stock (gold-stock) pairs.

Conclusions

In our paper we employ various time series analysis including DCC-GARCH, DECO-GARCH, wavelet coherence analysis and copula functions to investigate the relationship between East Asian stock markets and between East Asian stock markets and the prices of crude oil and gold.

We first investigates the Dynamic Conditional Correlations (DCCs) between eight emerging East Asian stock markets and the US stock market and analyses the dynamic equicorrelation among these nine stock markets. We find a significant increase in the conditional correlations and equicorrelation in the first phase of the global financial crisis. We refer to this finding as contagion from the US stock market to the emerging East Asian markets. We also find an additional significant process of increasing correlations and equicorrelation (herding) in the second phase of the global financial crisis. Further, we employ two new models, namely DCCX-MGARCH (a DCC Multivariate GARCH model with Exogenous Variables) and DECOX-MGARCH (a Dynamic Equicorrelation Multivariate GARCH model with Exogenous Variables), to identify the channels of contagion. We find that an increase in the VIX index increases the conditional correlations and equicorrelation, while increases in TED spreads decrease the conditional correlations of six emerging East Asian countries with the US. We compare the accuracy of the conditional correlation estimates of the DCC and DCCX models (or DECO and DECOX models) by constructing a loss function. We find that the DCCX (DECOX) model provides more accurate conditional correlation estimates than the DCC (DECO) model by extracting additional information from exogenous variables.

We then examines the interdependence and causality relationship between oil and East Asian stock returns from 1992 to 2015 and provides a fresh perspective on portfolio diversification benefits using wavelet coherence analysis. We find that oil prices and the East Asian stock market move in phase, and oil prices lead to stock returns in the long run.

We provide evidence that oil can reduce the risk in the short run, and the degree of risk reduction of oil-stock portfolio decreased over the long term. This study provides information that can guide investors in diversification efforts while investing in oil and East Asian stock markets.

Finally, we examines the interdependence of stock markets of East Asian countries and crude oil and gold prices across different time scales using the wavelet transform analysis and conditional copula functions. Most interdependence and tail dependence between oil and East Asian stock markets increases as time scales increase. The gold and East Asian stock interdependence is always weaker than those of oil-stock pairs. The tail dependence did not obviously increase in the short-term and midterm horizon and sharply increased in the long-term horizon. This study has implications for international investor to optimize the portfolio allocation.

Future research should explore the dynamic joint distribution of East Asian stock markets and the prices of oil and gold and compare the Value at Risk with and without the wavelet transform.

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