國立交通大學

管理科學系碩士班

碩士論文

公債市場之動態相關分析-以 **DCC** 模型為研究方法

Dynamic Correlation Analysis of Sovereign Debts with the Dynamic Conditional Correlation Model

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摘 要

本篇論文利用Engel (2002)提出的DCC模型及廖維苡(2008)所提出的DCCX 模型分析公債市場的動態信用風險相關性。本文分別使用日本、香港、南韓、泰國、台灣及美國等六國公債市場的信用價差週資料來衡量公債市場信用風險的狀況，並加入了芝加哥選擇權交易所(CBOE)的波動性指數(VIX)做為市場不確定性的代理變數。樣本期間從2000/11/1至2008/2/20。DCC模型估計結果證實公債市場之間相關具有時變的現象，且DCCX 模型的結果顯示市場不確定性會對於公債市場的信用相關程度產生顯著的影響，當不確定性增加時，風險的相關程度也會提高。因此在分析債券市場風險以及風險分散上，投資人可藉由觀察VIX的波動判斷市場間連結的變化。本篇論文的研究結果可為投資人資產配置及投資決策的一個參考依據。

關鍵詞：信用價差、DCC 模型、公債

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ABSTRACT

This paper investigates the dynamic correlation of credit risk of sovereign debts by the DCC model and the DCCX model. We use the credit spread as the proxy for credit risk. The credit spread data are 10-year sovereign bond yield of the US and five Asia countries – Japan, Hong Kong, South Korea (henceforth Korea), Thailand, and Taiwan – relative to the US 1-year treasury yield. Furthermore, we take CBOE volatility index (VIX) as the measurement of market uncertainty. The data begin on 2000/11/1 and end on 2008/2/20. The estimation by the DCC model indicates the time-varying correlation between credit spreads. The results also show that the market uncertainty has significant impact on the correlations. That is, the credit correlations between countries increase when the uncertainty of financial markets rise. International investors could estimate the connection of debt markets by investigating the variation of VIX. Our empirical results contribute to the management of asset allocation and the diversification of risks.

Keywords：credit spread, Dynamic Conditional Correlation Model, sovereign debts

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I. Introduction

Credit risk management has long been considered an important issue since the world financial markets started to grow and integrate. Investigation of credit quality is based on inspection of the credit or finance history from financial statements and historical data. Furthermore, because of the improvement of information transmission and closer trading relationship between countries, the contagion effect between financial markets has become worldwide and significant over time. That is, shock originating from one market actually transmits to other markets, which makes the credit management more complicated. Therefore, the credit risk correlations, which are the dependence among risks, become important issues in the research of risk management. The purpose of this study is to explore the credit risk relations among debt markets and to explain how the relations vary over time.

The sovereign debt markets provide high-quality data sources for the measurement of credit risk. Investigating price and yields involves a more quantitative analysis of credit quality characteristics. According to Bank of International Settlement, the total size of government bond markets had grown from 24,154.2 billion in 2006 to 26,200.7 billion dollars in September, 2007. Particularly, the Asia local currency government bond markets had grown rapidly in past years with 21% growth rate in

2007. Although debt credit contagion has a great impact on construction of credit-sensitive portfolios for the banking and investment management (see Zhou, 2001), it is a source of substantial instability. The observation of price and credit spread change of bonds directly recovers the credit variation. Theoretically, credit spread is always viewed as a measurement of credit risk for debt (Manzoni, 2002). There have been a lot of researches on the determinants of bond price and yield, especially on bond return and credit spread. Taking credit spread for example, macroeconomic and financial variables, such as GDP growth, inflation and stock market return, are considered crucial factors of credit spread change (see Collin-Dufresne, Goldstein and Martin, 2001).

The objectives of this study are to investigate the credit risk correlations among sovereign debts and the factors associated with the correlation of debts issued by sovereigns. To our knowledge, the phenomenon of contagion among financial markets is obvious that the crisis from one country may be triggered or extends to others. Suggested by existing literatures, credit risk is closely connected with the financial market uncertainty which could be reflected by the implied volatility of stock. Also, the importance of stock volatility on credit spread at the aggregate level has also been discussed extensively in the literature (see Cambell and Ammer, 1993). To proxy uncertainty, economic variables from the US market are widely taken as the world factors because the US financial markets have great influence on emerging countries. For our purpose of analysis credit risk correlation, the financial markets factors from the US are adopted. Thus, the implied volatility from equity index options, specifically the Chicago Board Options Exchange Volatility Index (henceforth VIX), is used to measure the uncertainty of financial market and its influence on the credit spreads correlations.

Since the credit spread, like default rate, shows to be not constant over time (see Dungey, Martin and Pagan, 2000), it requires an approach which is capable of capturing time-varying behavior of credit spread as well as the exogenous variables. For the past few years, the GARCH family models have been used widely in time-series studies. Engle (2002) proposed the dynamic conditional correlation model (the DCC model), which is modification of multivariate GARCH model, to study dynamic correlation between assets. In our study, we also adopt the modified DCC model, called DCCX model, proposed by Liao (2008). This model allows adding an exogenous variable while we estimate conditional correlation. As we described in previous paragraph, the exogenous variable is VIX as measurement of market uncertainty to investigate the variation of correlations (see Connolly, Stivers and Sun, 2005).

This paper provides a new perspective and methodology to analyze credit spread. Credit spread is always considered a proxy for credit risk, which had been use to estimation the credit correlation between markets. However, this is the first research to investigate the dynamic relation between credit spreads and also the determinants. The empirical results of our study present that there are dynamic correlations among Asian debts markets and among those with the US. The standard and modified DCC models provide estimation of dynamic correlations and help explain for the major economic issues. The results from the DCCX model show that the credit correlation tends to be positively related with VIX. That is, the debts markets connect closer when crisis occurs and economic events happen. Works on credit correlation are beneficial from preventing asset value loss on one side and from well diversifying risk of portfolio on the other side. The results will assist those responsible for managing the risks of sovereign debt as well as diversifying portfolio assets allocation. Besides, investors would benefit from consideration of market uncertainty while they analyze credit risk and make decisions.

The remainder of this paper proceeds as follows. The relevant literatures about credit risk, cross-market hedge and methods are reviewed in section II. In section III, we provide the methodology applied in our study. It includes DCC and DCCX approaches associating with relevant literatures and models. All the empirical results and discussion of estimations are listed in section IV. The conclusion is given in the last part of Section V.

II. Literature Review

In this section we provide a review of literatures related to objectives and methods of our research. Baig and Goldfajn (1999) study the correlation between Asian countries respective equity and sovereign bonds markets, testing if the correlations in various markets increase significantly during the crisis period. The credit spreads over U.S. Treasury bill yield for Indonesia, Korea, Malaysia, Philippines, and Thailand is taken as proxies for credit risk. The results indicate the cross-country correlations are extremely significant. Also, there is a significant increase in correlation coefficients during the Asian crisis, concluding that there was a contagion effect among the Asian debt markets. It suggests that sovereign debt markets are more prone to be driven by contagion factors.

In sight of Baig and Goldfajn (1999), this section is divided into three parts. First, we review the papers work on modeling the credit spread of debt, as the measurement of credit risk. The second part is about the papers modeling credit relation between markets and determinant related to the relations. The last part is about literatures of GARCH family models, including the DCC and the DCCX model, and their empirical studies related to the approach applied in this paper.

2.1. The modeling of credit spread

The most of credit spread variation is related to credit risk of debts. Investors require a higher premium for the riskier debts so the debts with more risky have higher yields and also spreads. Cantor and Packer (1996) investigate the impact of sovereign rating announcements-the risk assessment assigned by credit rating agencies-on credit spreads of sovereign bonds. A regression of the log of these countries' bond spreads against their average ratings, which explain 92 percent of variation, shows that ratings have considerable power to explain sovereign credit spreads. The sovereign spreads tend to increase when ratings decline. Other factors related to credit spread are macroeconomics variables and shocks from stock market.

In the recent finance-related literatures, much attention have been drawn to models of the credit spreads (see Elton, Gruber, Agrawal and Mann, 2001). Collin-Dufresne, Goldstein and Martin (2001) investigate the determinants of credit spread changes of corporate bonds. They assume that the debt is like a short position in a put option whose values increase with volatility measured by VIX. This prediction is that increased volatility increases the probability of default. The result of this study propose factors, such as changes in the spot rate, changes in the slope of the yield curve, changes in volatility, and changes in the business climate, have ability to explain credit spread. Particularly, changes in volatility have asymmetrically influence on credit spread: an increase in volatility has a great impact on spreads while a decrease does not.

There are also papers which study about the determinants of sovereign bonds. Duffie, Pedersen and Singleton (2003) study the determinants of the Russian debt credit spread, the yield differential across different Russian bonds. The credit spread of Russian spreads were high in 1995 when there are significant uncertainty regarding its ability to repay the debt and also high until the default in August, 1998. They find that Russian credit spreads vary over time, respond to political events, and are negatively related to Russian foreign currency reserves and the oil price.

Westphalen (2001) investigates the determinants of credit spread changes of sovereign bonds by regression. The historic volatility over the last 20 trading days of the local MSCI country stock index is a proxy for the volatility. For different countries, the explanations of regressions are ranged from 10.8% for Emerging Europe to 21.5% for Africa. The rating classes, one of the variables in the regression, can explain more variation in the long- term bonds than in the short-term bonds. That is, the factors related to credit spread are different based on credit risk. Also, changes in local stock market volatility, proxy for change in the volatility of country, have a significantly positive effect on the spreads of sovereign bonds. It suggests that higher volatility increase the risk. The country probably hit the triggering level of default.

The variation of credit spread is not constant overtime. Most of the models cannot explain the time-series behavior of credit spreads (see Cooper and Mello, 1988). Dungey, Martin and Pagan (2000) and Manzoni (2002) use time-varying volatility model to capture behavior of credit spread. Dungey, Martin and Pagan (2000) take AR (2)-GARCH (1, 1) and factor model to model credit spreads of sovereign debts and their latent factors. All countries feature strong positive autocorrelation and persistence of volatility to shocks. Furthermore, they find that the world factor has dominant influence on sovereign spreads when it comes to factor model. For example, the world factor accounts for nearly 90% of total volatility for Germany, Canada and the UK, which indicate world financial factor has a great impact on credit spreads. Manzoni (2002) follows time-series approach to study sterling Eurobonds credit spreads and the force drives the change and volatility of credit spread. The time-series properties of credit spread provide strong evidence of nonlinearities. Also, the macroeconomic and financial factors have driven changes in the sterling Eurobond credit spreads. Particularly, the return and volatility from stock market carries significant influence on credit spreads.

2.2. Cross-market hedge

To our knowledge, the correlation between markets in Asia is proved by several studies. Solnik (1996) studies the correlation between Asia stock markets and between

Asia bond markets to indicate that international correlation increase in the periods of high market volatility and strongly affected by national factors. Studying for crisis, Masih and Masih (1997) present the fact that the correlation of the international markets revealed obviously after the crash of the New York Stock Exchange in 1987, the financial crisis in Mexico in 1994 and the Asian Financial Storm from 1997 to 1998. Baig and Goldfajn (1999) also show the significant correlation among Asia stock, currency, and bond markets.

Chiang, Jeon and Li (2007) investigate the stock market contagion in eight Asian countries and the US as well. The results show significant contagion effects that the correlations for any pairs of countries increase after Asian crisis. According to the results, the gain from international diversification by holding a portfolio consisting of diverse stocks from these contagion countries declines since these stock markets are commonly exposed to systematic risk. Also, this study suggests that both investors and international rating agents play significant roles in shaping the structure of dynamic correlations in the Asia markets.

Moreover, in recent studies, the cross-market credit correlation is studied for construction of portfolios and international investment. The literatures suggest that the credit correlation exists under certain situations and has some characteristics. For example, firms in the same industry (region) often have higher default correlations than those in different industries (regions). Zhou (2001) develops a model to calculate default correlation and joint default probability of two firms to calculate the probability of a two-dimensional stochastic process passing a boundary. The model theoretically implies that the high credit quality implies a low default correlation which is consistent with the well-known empirical feature regarding the relation between default correlation and credit ratings. Also, the default correlation and the asset level correlation are positive related. That's why firms in the same industry (region) often have higher default correlations than those in different industries (regions). Also, because the time of peak default correlation depends on the credit quality of the underlying firms which is time-varying, the default correlation is dynamic. Loffler (2003) estimates default correlation based on the joint distribution of assets values and shows similar results.

The Latin American and Asian countries credit correlation is worth focusing on because those emerging countries are more risky than developed countries. Cowan and Cowan (2004) suggest that it is more worthwhile to focus on the lower grade portfolios which are sensitive to changes in default correlations. Furthermore, the magnitude of default correlation increases as the internally assigned risk grade declines. They study the credit correlation of subprime lenders under loan portfolio, because this kind of portfolio carries greater risk of default and therefore compensates lenders with higher credit spread.

To figure out factors related to credit quality, Weigel and Gemmill (2006) have extracted the distance-to-default implied by bond prices, for Argentina, Brazil, Mexico and Venezuela, to investigate the impact of global, regional and country-specific factors on creditworthiness. Overall, the results show that global and regional factors are far more important than country-specific factors in determining changes in creditworthiness for these four emerging-market countries. It also considers the S&P 500 volatility as a proxy for global market uncertainty. The results indicate that it is positive and significant for credit quality, which is consistent with the modeling of credit spreads. It indicates that the dependence of emerging markets on industrial countries increase because of globalization.

Actually, the cross-market hedge is also related to the uncertainty. Chordia, Sarkar and Subrahmanyam (2001) explore both trading volume and spreads in the stock and bond markets respectively from June 1991 to December 1998 to find the evidence consistent with linkage between dynamic cross-market hedging and uncertainty. They ponder over the Asian crisis in 1997 and the Russian default crisis in 1998, and the results suggest that greater market uncertainty during the crisis periods leads to an dramatical changes in correlation between stock and bond spread and volume relevant to normal times, and linkages between stock and bond market liquidity are significantly stronger in the crisis periods. Thus, the uncertainty of financial market is a critical factor while we consider market correlation.

Connolly, Stivers and Sun (2005) study whether stock-government bond return relation in nine European countries from 1992 to 2002 varies due to the influence of stock market uncertainty which is measured by equity implied volatility. The stock market uncertainty is measured by the implied volatility from equity index options, specifically the Chicago Board Options Exchange's Volatility Index (VIX). The results indicate bond returns tend to be high during days when implied volatility increases. They also find a negative relation between the uncertainty measures and the future correlation of stock and bond returns that the correlation of daily stock and bond returns swing from significantly positive in low uncertainty periods to significantly negative in high uncertainty periods in most countries. This study presents additional evidence supporting these stock market uncertainty effects may stem from cross-market rebalancing. When considering cross-market pricing influences, variation in stock market uncertainty (as measured by stock volatility) is likely to be more important than variation in bond market volatility.

According to the articles mentioned above, the contagion is significant for financial markets and regions as well as the credit correlation. Because equity implied volatility can be determinant of credit spreads as well as the measurement of influence of market uncertainty which has an impact on cross-market hedge, it is taken as an exogenous variable while we explain the variation of credit correlations. The US stock market volatility is adapted because of dependence of emerging markets on industrial countries increasing due to globalization. Therefore, our study of credit contagion of Asia countries will take credit spread of sovereign debts as the measurement of credit quality and VIX as the uncertainty of world financial markets. However, the credit spread analysis is lack of time-varying. Our study applies an appropriate model to improve estimation.

2.3. The Development of the Methodologies-Dynamic Conditional Correlation model

The Autoregressive Conditional Heteroskedasticity (ARCH) proposed by Engle (1982) is among the most widely used time-varying covariance models. ARCH model which would be possibly the most important innovation in modeling markets volatility changes adopts the effect of past residuals and helps explain the volatility clustering phenomenon. Bollerslev (1986) proposes Multivariate Generalized Autoregressive Conditional Heteroskedasticity model (GARCH) which opens a new field in research of volatility and is widely applied in research of financial and economic time series (see Bollerslev, Chou and Kroner, 1992). The GARCH models are with flexible adoption of dynamic of volatility ant it does simplify of estimation. It also extends to different models, for example, see Nelson (1991) and Brandt and

Jones (2005) for EGARCH models.

Large time-varying covariance matrices are needed in portfolio management. Bollerslev (1990) introduced the constant conditional correlation multivariate GARCH model for estimation assets correlations. The assumption of constant correlation makes estimation a large model which is feasible. However, Tsui and Yu (1999) find the constant correlation assumption is rejected for certain assets.

Alexander (2000) proposes the factor GARCH model for estimation of large covariance matrices with limited number of factors. However, this approach is constrained by the difficulty in interpreting the coefficients on the univariate GARCH model. Engle (2002) proposes dynamic conditional correlation model to improve the weakness of CCC model. The correlation is time-varying rather than constant when it is estimated by two-stage estimation. This model has a clear advantage over multivariate GARCH models in that the number of parameters to be estimated in the process which is independent of the number of series to be correlated. Cappiello, Engle and Sheppard (2006) develop asymmetric DCC to allow news impact on correlation estimation. Equity returns show strong evidence of asymmetries in conditional volatility while little is found for bond returns.

Liao (2008) proposes a Modified Dynamic Conditional Correlation model (the DCCX model) to estimate the time-varying correlations between stock and bond returns. The DCCX model allows adding exogenous variables when we estimate correlation. The result shows a high positive correlation between returns of the S&P500 and 10-year-treasury-bonds. Also, estimated by the DCCX model, it suggests that uncertainty from stock market has important influences on the correlation.

III. Methods

The main objectives of this study are to examine the credit correlations between sovereign bonds by dynamical conditional model, so called DCC model. It was first proposed by Engle and Sheppard (2001) and then extended by series of papers such as Engle (2002) and Cappiello, Engle and Sheppard (2006). There are two stages of the estimation- the first is to obtain volatility and residual for each series by univariate GARCH, and the second is to transform standardized residual to estimate conditional correlation estimators- by maximum likelihood method. The DCC model is a new class of multivariate GARCH models which have the flexibility of univariate GARCH but not the complexity of multivariate GARCH (see Engle, 2002). Furthermore, the DCCX model is the modification from the DCC model. The only difference between two models is that the DCCX model allows us to include the additional explanatory variables in the equation to investigate the determinants of correlations. This improvement helps us to explain the behavior of correlations. This section provides the overview of the models

3.1. The Dynamic Conditional Correlation (DCC) Model

The conditional correlation between two variables, $r_{1,t}$ and $r_{2,t}$, that each have mean zero is defined to be:

$$\rho_{12,t} = \frac{E_{t-1}(r_{1,t}r_{2,t})}{\sqrt{E_{t-1}(r_{1,t}^2)E_{t-1}(r_{2,t}^2)}} \quad (1)$$

As equation (1) presents, the estimation is based on previous information. However, it requires premature data and assigned equal weights for every previous lags which complicates the process of estimation.

Bollerslev (1990) introduces the constant conditional multivariate GARCH model specification (CCC model), where univariate GARCH is fitted to each series and then transformed residuals are used to estimate a correlation matrix. A multivariate conditional covariance is defined as follows:

$$H_t = D_t R D_t \quad (2)$$

$$D_t = diag\left\{\sqrt{h_{i,t}}\right\}, \quad (3)$$

H_t is covariance matrix, and R is sample correlation matrix. D_t is the $k \times k$ diagonal matrix of time varying standard deviations from univariate GARCH model. D_t is with $\sqrt{h_{i,t}}$, which is the square root of conditional variance of the i^{th} series, on i^{th} diagonal. We propose to write the elements of D_t as estimated by GARCH model:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t\text{-}1}^2 + \beta_i h_{i,t\text{-}1} \quad (4)$$

The model with assumption of constant correlation ensures the feasibility of estimation and positive definition of parameters. However, recent papers find that constant correlation could be rejected for certain assets. Therefore, Engle (2002) generates and extends the CCC model into a new class of estimator which allows for correlations to change over time. The main improvement is R_t could be time-varying rather than constant.

The dynamic conditional correlation GARCH model proposed by Engle (2002) is defined as follows:

$$H_t = D_t R_t D_t \tag{5}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{6}$$

$$Q_t = S \circ (\iota\iota' - A - B) + A \circ Z_{t-1} Z_{t-1}' + B Q_{t-1}, \tag{7}$$

or in a bivariate case,

$$\begin{bmatrix} q_{ii,t} & q_{ij,t} \\ q_{ji,t} & q_{jj,t} \end{bmatrix} = (1-a-b)\begin{bmatrix} 1 & \bar{q}_{ij} \\ \bar{q}_{ij} & 1 \end{bmatrix} + a\begin{bmatrix} z_{i,t-1}^2 & z_{i,t-1}z_{j,t-1} \\ z_{j,t-1}z_{i,t-1} & z_{j,t-1}^2 \end{bmatrix} + b\begin{bmatrix} q_{ii,t-1} & q_{ij,t-1} \\ q_{ij,t-1} & q_{jj,t-1} \end{bmatrix} \tag{8}$$

where $\bar{q}_{ij} = E(z_{i,t} z_{j,t})$.

It can be expresses in the mean reverting process given by:

$$q_{ij,t} = (1-a-b)\bar{q}_{ij} + a z_{i,t-1} z_{j,t-1} + b q_{ij,t-1} \tag{9}$$

H_t is covariance matrix and D_t is the $k \times k$ diagonal matrix of time varying standard deviations from univariate GARCH model with $\sqrt{h_{i,t}}$ which are same as the CCC model. Furthermore, R_t is a possible correlation matrix containing the conditional correlation of the pair-wise standardized residuals, $z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$. Q_t , which contains elements q_{ij}, and S are the conditional and unconditional covariance of standard residuals $z_{i,t}$ and $z_{j,t}$, respectively. A and B are diagonal parameter matrices and $\circ$ denotes Hadamard matrix product operators. ι is vector of one. Q_t^{*-1} is diagonal matrix composed of square root of diagonal elements of Q_t:

$$Q_t^{*-1} = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 & \ldots & 0 \\ 0 & \sqrt{q_{22}} & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \ldots & \sqrt{q_{kk}} \end{bmatrix}$$

If A and B are zeros, DCC model will revert to the structure of the CCC model. The related papers show that Q_t will be positive definite as it is a weighted average of a positive definite matrix S, a positive semi-definite matrix $Z_{t-1}Z_{t-1}'$ and a positive definite matrix Q_{t-1} (see Engle and Sheppard (2001)). As long as the covariance matrix Q_t is positive definite, R_t is positive definite which contains ones on the diagonal and every other element ≤ 1 in absolute value. The conditional correlation coefficient is defined as:

$$\rho_{ij,t} = q_{ij,t} \Big/ \sqrt{q_{ii,t} q_{jj,t}} \qquad (10)$$

For conditional covariance, it needs to use the conditional correlation in equation (10) and the conditional standardize residuals in which.

3.2. The Modified Dynamic Conditional Correlation (DCCX) Model

The DCC model has been widely used and verified into different versions such as asymmetric DCC (see Cappiello, Engle and Sheppard (2006)). The DCCX model is with the same idea as DCC model and modifies the correlation evolution equation to be:

$$H_t = D_t R_t D_t \tag{11}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{12}$$

$$Q_t = S \circ (\iota\iota' - A - B) - C\bar{X} + A \circ Z_{t-1} Z_{t-1}' + B Q_{t-1} + C \circ X_{t-1}, \tag{13}$$

$$Q_t^{*-1} = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 & \dots & 0 \\ 0 & \sqrt{q_{22}} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & \sqrt{q_{kk}} \end{bmatrix}$$

or in bivariate case,

$$\begin{bmatrix} q_{ii,t} & q_{ij,t} \\ q_{ji,t} & q_{jj,t} \end{bmatrix} = (1-a-b)\begin{bmatrix} 1 & \bar{q}_{ij} \\ \bar{q}_{ij} & 1 \end{bmatrix} - \begin{bmatrix} 0 & c\bar{x} \\ c\bar{x} & 0 \end{bmatrix} + a\begin{bmatrix} z_{i,t-1}^2 & z_{i,t-1} z_{j,t-1} \\ z_{j,t-1} z_{i,t-1} & z_{j,t-1}^2 \end{bmatrix} + b\begin{bmatrix} q_{ii,t-1} & q_{ij,t-1} \\ q_{ij,t-1} & q_{jj,t-1} \end{bmatrix}$$
$$+ c\begin{bmatrix} 0 & x_{t-1} \\ x_{t-1} & 0 \end{bmatrix} \tag{14}$$

$$q_{ii,t} = (1-a-b) + a z_{i,t-1}^2 + b q_{ii,t-1} \tag{15}$$

$$q_{jj,t} = (1-a-b) + a z_{j,t-1}^2 + b q_{jj,t-1} \tag{16}$$

$$q_{ij,t} = (1-a-b)\bar{q}_{ij} - c\bar{x} + a z_{i,t-1} z_{j,t-1} + b q_{ij,t-1} + c x_{t-1} \tag{17}$$

H_t, D_t, R_t, Q_t, and Q_t^{*-1} remain the same meanings as the DCC model. A, B, and C are $k \times k$ diagonal parameter matrices. The variable X is the exogenous variable included to investigate the correlation between series. X_{t-1} represents the determinant of X at the time t-1, and $\bar{X}$ is unconditional expectation of X. The mean reverting requires to subtract the long-term expected mean of X. We refer to this model as DCCX.

The DCC model was assigned to allow two stage estimations of conditional covariance matrices. At the first stage, univariate volatility model is fitted to each time series for obtaining residuals. At the second stage, residuals, transformed by their standard deviation estimated during the first stage, are used to estimate the parameter of the conditional correlation.

The log-likelihood function of this estimator can be written:

$$\begin{aligned} L &= -\frac{1}{2}\sum_t (k\log(2\pi) + \log|H_t| + r'_t H_t^{-1} r_t) \\ &= -\frac{1}{2}\sum_t (k\log(2\pi) + \log|D_t R_t D_t| + r'_t D_t^{-1} R_t^{-1} D_t^{-1} r_t) \\ &= -\frac{1}{2}\sum_t (k\log(2\pi) + 2\log|D_t| + \log|R_t| + Z'_t R_t^{-1} Z_t) \\ &= -\frac{1}{2}\sum_t (k\log(2\pi) + 2\log|D_t| + r'_t D_t^{-1} D_t^{-1} r_t - Z'_t Z_t + \log|R_t| + Z'_t R_t^{-1} Z_t) \end{aligned} \tag{18}$$

where $Z_t \sim N(0, R_t)$ are the residual standardized by their conditional standard deviation.

Let the parameters in model be written in two groups, (θ_1, θ_2). The elements of $\theta_{1,i}$ correspond to the parameters of the univariate GARCH model for the i^{th} series,

$\theta_{1,i} = (\omega_i, \alpha_i, \beta_i)$. θ_2 corresponds to additional parameters in R_t. The log-likelihood function could be divided into two parts:

$$L(\theta_1, \theta_2) = L_{vol}(\theta_1) + L_{corr}(\theta_1, \theta_2). \tag{19}$$

The former represents the volatility estimation at the first stage:

$$\begin{aligned} L_{vol}(\theta_1) &= -\frac{1}{2}\sum_t (k\log(2\pi) + \log|D_t R_t D_t| + r'_t D_t^{-2} r_t) \\ &= -\frac{1}{2}\sum_t (k\log(2\pi) + \sum_{i=1}^{k}(\log(h_{i,t}) + \frac{r_{i,t}^2}{h_{i,t}})) \end{aligned} \tag{20}$$

which is the sum of log-likelihood function of the individual GARCH model for the series. This can be jointly maximized by separately maximizing each term. The second part of equation (19) is estimation of correlation component, conditioning on the parameters in the first stage:

$$\begin{aligned} L_{corr}(\theta_1, \theta_2) &= -\frac{1}{2}\sum_t (k\log(2\pi) + \log|D_t R_t D_t| + r'_t D_t^{-1} R_t^{-1} D_t^{-1} r_t) \\ &= -\frac{1}{2}\sum_t (k\log(2\pi) + 2\log|D_t| + \log|R_t| + Z'_t R_t^{-1} Z_t - Z'_t Z_t) \end{aligned} \tag{21}$$

Since the estimation is conditioning on θ_1, it is often easier to exclude the constant terms and simples to:

$$L_{corr}(\theta_1, \theta_2) = -\frac{1}{2}\sum_t (\log|R_t| + Z'_t R_t^{-1} Z_t - Z'_t Z_t) \tag{22}$$

Engle (2002) proposes that it can perform the estimation by qusi-maximum likelihood estimation (QMLE) to obtain consistent parameter estimates. Although the estimations are consistent, they are inefficient. The estimation in first stage can pick up θ_1 to satisfy equation (19). Given the θ_1 in fist stage, it can be maximized equation (21) with respect to optimized θ_1 and θ_2. The two-stage approach to maximizing the likelihood is to find the following:

$$\hat{\theta}_1 = \arg\max\left\{L_{vol}(\theta_1)\right\} \tag{23}$$

$$\max_{\theta_2}\left\{L_{corr}(\hat{\theta}_1,\theta_2)\right\} \tag{24}$$

The DCCX model follows the same stages of estimation as DCC model. It firstly estimates volatility for each series and obtain standardized deviation. For all series, the GARCH volatility structure is using at stage one:

$$r_{i,t} = \varepsilon_{i,t}, \varepsilon_{i,t}\left|\mathrm{I}_{t\text{-}1} \sim N(0,h_{i,t}), i=1,2,\ldots,6\right. \tag{25}$$

$$h_{i,t} = \omega_i + \alpha_i\varepsilon_{i,t\text{-}1}^2 + \beta_i h_{i,t\text{-}1} \tag{26}$$

$$z_{i,t} = r_{i,t}/\sqrt{h_{i,t}} \tag{27}$$

IV. Results

4.1. Sample

The investigated data set consists of credit spreads calculated by 10-year sovereign bond yield of the US and five Asia countries - Japan, Hong Kong, South Korea (henceforth Korea), Thailand, and Taiwan – relative to US 1-year treasury yield. Japan, Korea, Thailand and Hong Kong have the largest amount of local currency Bond Markets in Asia despite China[1]. The yield data begin on November 1, 2000 and end on February 20, 2008 reported by DataStream, given the sample size of 382 observations.

Moreover, to investigate the determinants of correlations between two credit spread changes, Chicago Board Options Exchange Volatility Index (VIX) is included as proxy of uncertainty of financial market which is suggested by prior literature. The VIX is a key measure of market expectations of near-term volatility conveyed by the S&P 500 stock index option prices. Introduced in 1993, it initially was a weighted average of implied volatility of eight at-the-money put and calls options on S&P100 index. In 2003, it was expanded to a broader index, S&P 500, to estimate the implied volatility of at-the-money index option, with 30 days to expiration. The VIX is a

1 The amount of bond market size in 2007 for US, Japan, Korea, Thailand and Hong Kong are 6,480.8, 6,879.28, 722.11, 107.47 and 107.52 in billions of US dollars.

widely used measure of market risk[2]. Investors expect the volatility of market to increase when the VIX index goes up. The higher the ratio, the lower is the investors' confidence. It has been considered to be sentiment and market volatility by the world's premier of investor. The data of VIX is obtained from DataStream as well. Here, the natural log of VIX ($\ln(vix_{t-1})$) at the period t-1 is including in the process of estimating dynamic conditional correlation[3].

4.2. Descriptive statistics

To calculate the credit spreads for bond i at time t, we use the US Treasury bond. The credit spread is defined as 10-year bond yields over US treasury yield, and credit spread change is defined as first-difference of credit spread as Cantor and Packer (1996):

$$\text{Credit Spread} = \text{yield on sovereign bond}_{i,t} - \text{yield on US treasury bond}$$

<Figure 1 is inserted about here>

Figure 1 shows the graphs of credit spreads and the changes of six countries over the sample period. The credit spread and the volatility fluctuate over time and seem to arise in the late 2001, 2003 and 2007. The 911 territory attack of 2001 damages the

[2] CBOE volatility index is referred to as the investor fear gauge.

[3] The MSCI world index is considered as proxy for world economic climate when we choose exogenous variables. However, the results of this variable show statistically insignificant impact on the correlation of credit spreads. The data are not listed in the following tables.

worldwide economic markets. In 2003, because the US government urges to get rid of recession and afford the expenditure used in the arms with Iraq, it issued debts with higher yields which also increases the credit spreads in domestic debt market as well as Asian countries which are closely related with the US. In 2007, the subprime mortgage crisis also increases the credit risk in debt markets. The time-varying characteristics and volatility cluster evidence suggest capturing the time-varying volatility series by the GARCH model. Table 1 provides descriptive statistics of the credit spread changes and unconditional correlation among countries and VIX.

<Table 1 is inserted about here>

In Panel A, the mean of every credit spread changes are positive over the sample period except Hong Kong. By investigating standard deviation, it shows that Korea's spread change is more volatile than any other country. Almost all series present positive skewness and excess Kurtosis. Jarque-Bera[4] for null hypothesis is far beyond the critical value at 5% level, which suggests that the series are not normal distribution. In sum, the characteristic of fat-tail and also statistics of Jarque-Bera indicates the non-normality distribution.

Information on the contemporaneous relationships of the spreads across countries

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[4] The Jarque-Bera test is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness. The test statistic *JB* is defined as $\frac{n}{6}(S^2 + \frac{(K-3)^2}{4})$, where *S* is the skewness, *K* is the kurtosis, and *n* is the number of observations.

as well as those between VIX is given by the unconditional correlation in Panel B. It suggests that there is some commonality in the time series properties of the spreads. The correlations between two Asian countries are higher than correlations between those with the US, which indicates the connection of markets within the Asian continent is closer. The results are consistent with Zhou (2001) that markets in the same region often have higher default correlations than the firms in different regions. Particularly, the correlation between Taiwan and Japan is extremely obvious. Furthermore, VIX is negatively related to credit spreads. This result is consistence with research before (see Westphalen, 2001). When the market uncertainty goes up, the credit quality of sovereign bond moves in the opposite direction. To sum up, the identification of unconditional correlations is important before we take a look into the time-series analysis of dynamic conditional correlations.

4.3. Empirical analysis

As mentioned previously, the DCC model, which needs two stages of estimation, is used to estimate dynamic conditional correlation between assets. At the stage 1, the credit spread series fit the univariate GARCH for estimating the volatility and standard deviation of each series. Then, at stage 2, it processes to obtain the conditional correlation by standard deviation and $\bar{q}_{12} = E(z_{1,t}, z_{2,t})$. In this study, we proposed the standard DCC model and the modified DCC model (DCCX). The only difference between DCC and DCCX is that the DCCX model includes an extra exogenous variable, VIX, when we estimated correlations. Table 2 provides two-stage estimation results of the DCC models of credit spread changes by maximum likelihood method over the sample period.

<Table 2 is inserted about here>

In Panel A of Table 2, we could see the coefficients of estimation at stage 1 are all significant at 5% level except some coefficients of constant parameters. Specifically, it implied that the volatility of spread change is mainly driven by its own volatility on the previous period- as indicated by the size of $\hat{\beta}$, which measures the long-term persistence in volatility. The strong persistence of volatility to shocks is in the range of 0.690 and 0.918 while the rather weak effects of $\hat{\alpha}$ are in the range of 0.071 and 0.398. The sum of estimated coefficients ($\hat{\alpha}+\hat{\beta}$) is close to unity for all the cases, implying that the volatility display a highly persistent fashion.

After fitting the series to GARCH (1, 1), we investigate correlation estimation in Panel B. First, in the DCC model, the results present all coefficients are significant under 95% confidence except $\hat{a}$. The results show that the correlations are significantly dynamic. Second, the estimation of the DCCX model concerning VIX shows that all of $\hat{b}$ are significant at 1% or 5% level. Moreover, there are twelve out of fifteen coefficients ($\hat{c}$) of exogenous variable, $\ln(\text{vix}_{t-1})$, are significantly positive at 1% or 5% level, which means correlations between credit spread changes tend to vary in an opposite direction of VIX during periods. That is, the credit correlations among countries increase when the uncertainty of financial markets is high.

<Figure 2 is inserted about here>

Figure 2 shows that all pair-wise correlations estimating by the DCCX model. The correlations are fluctuating over time and have similar patterns.

<Figure 3 is inserted about here>

Panel A in figure 3 indicates more clearly that the average correlations between two Asian countries are around 0.4 to 0.8, which is higher than the average correlations between Asian and the US that are around 0.1 to 0.6. The results are consistent with the unconditional correlation in Table 1 that the connection of markets within the Asian continent is rather closer than those with the US. From the average correlation graphs between countries in Panel B, we can see there is a significant peak at the last season of 2001 which is the time after the 911 terrorist attacks. There is a higher correlation from 2004 to 2005. Since the bloom of world economic after 2004, especially in emerging markets, the credit quality is improved in debt markets. The credit spreads are all downside in the same direction, thus, the correlation is increasing. The significant ascending correlation from 2007 summer until the end of sample period coincides with the subprime mortgage crisis which causes the higher credit risk of debt markets. The results are consistent with literatures that suggest the correlations for any pairs of countries increase after the crisis. Compared with Panel B, the VIX graph in Panel C also increases in late 2001 and 2007. It provides same empirical results in DCCX model that correlations are moving is the same direction with market uncertainty.

We turn to simple OLS regressions to explore the determinants of credit spread correlation again. The following equation is used to test how these variables affect correlations:

$$corr_{i,j,t} = a_0 + a_1 corr_{i,j,t\text{-}1} + a_2 \ln(vix_{t\text{-}1}) + v_t \tag{28}$$

The dynamic conditional correlations estimated by the DCC model ($corr_{i,j,t}$) regress with correlation in the period t-1 ($corr_{i,j,t-1}$) and proxy for market uncertainty, $\ln(\text{vix}_{t\text{-}1})$. The results of regressions estimated by OLS are reported in table 3.

<Table 3 is inserted about here>

The regressions can explain large part of correlations with the range of 71% and 95%. The correlations are mainly determined by correlation in the last period. All of the coefficient, a_1, are significantly positive. Furthermore, the correlations are positively and significantly influenced by $\ln(vix_{t-1})$ under the 5% or 10% level except few pairs. Specifically, the correlation would slightly increase when the uncertainty increases. This result is consistent with the DCCX model.

4.4. Joint volatility and correlation dynamics

For many financial decisions and strategies like risk management and pricing derivatives, the relationship between volatilities and correlations are important. The high correlation values associated with the extreme volatility in the underlying markets would make international diversification benefits disappear (see Cappiello, Engle and Sheppard, 2006). If correlations move in the same direction, then risks in the long run are greater than they seem in the short run. For the investors who diversify internationally, it would be beneficial to identify markets where the correlations are less sensitive to values of the volatilities in these markets. After investigating credit correlation between two countries, here we examine the average relations of volatility and correlation for the underlying country. We also examine whether the relations increase or decrease after we consider VIX as we estimate correlations. We define the average correlation (φ_i) as follows:

$$\varphi_i = \frac{1}{k-1}\sum_{j=1,i\neq j}^{k} \frac{\sum_{t=1}^{T}(h_{it}-\bar{h}_i)(\rho_{ijt}-\bar{\rho}_{ij})}{\sqrt{\sum_{t=1}^{T}(h_{it}-\bar{h}_i)^2\sum_{t=1}^{T}(\rho_{ijt}-\bar{\rho}_{ij})^2}} \tag{29}$$

For country i, h_{it} is its variance, and ρ_{ijt} is its associated pair-wise correlation with other the countries. Table 4 reports the value of φ_{i} relative to each spread series.

<Table 4 is inserted about here>

In table 4, φ_i are positive which suggest that volatility and correlation are move together. For example, as Japan volatility rise, all its pair-wise spread correlations increase as well. Moreover, the indicators in the right column are lower than those in the left one. To take average of all countries, the correlation decrease from 0.368 to 0.3. That is, it benefits from considering uncertainty of financial markets when estimating correlation between markets. This will helps reduce risk in the long run.

4.5. Implication in international diversification

From the application above, we could see it is important for investors to deliberate the influence from uncertainty of financial markets. Another application is to use the estimation of correlation in portfolio construction. We assume there is a minimum-variance portfolio containing two assets, one is an Asian bond and the other is a US bond. From the DCCX model, the dynamic conditional correlation concerning VIX is generated before. To take average of conditional variance of Asia bonds and average of correlation between the Asian countries and the US, it could estimate the weights of two assets by following equations:

$$\text{Min} \quad h_t = w_{a,t}^2 h_{a,t} + w_{u,t}^2 h_{u,t} + 2w_{a,t} w_{u,t} \sqrt{h_{u,t} h_{a,t}} \rho_t \tag{30}$$

$$w_{a,t} = \frac{h_{u,t} - \sqrt{h_{u,t} h_{a,t}} \rho_{a,u,t}}{h_{a,t} + h_{u,t} - 2\sqrt{h_{u,t} h_{a,t}} \rho_{a,u,t}} \tag{31}$$

$$w_u = 1 - w_a \tag{32}$$

w_a and w_u are portfolio weight of Asian and the US sovereign debts. h_a and h_u are variance. h_t and ρ_t are covariance and correlation between Asian and the US sovereign debts.

We would like to measure how natural log of VIX in the last period affects the weights of portfolio by regressions, and then, we can identify how much weight investors should increase or decrease for certain assets. The weights are regressive against the natural log of VIX in the last period:

$$w_{a,t} = \alpha + \beta \ln(vix_{t-1}) + \varepsilon_t \tag{33}$$

$$w_{u,t} = \alpha + \beta \ln(vix_{t-1}) + \varepsilon_t \tag{34}$$

<Table 5 is inserted about here>

The results show in Table 5. It should decrease weight by 7.6% in the Asia bond if VIX increase by 1%, the US bond weight otherwise. That is, when the market uncertainty goes up, the investors should add more on US market instead of Asia. This active strategy helps manage portfolio weight avoid risks according to different world economic situations.

V. Conclusion

It is particularly important to check how credit correlations among countries vary over time for risk diversification and portfolio management. In this study, we use credit spreads of five Asian countries and the US sovereign debts relative to US 1-year treasury yield as the measurement of credit risk to examine correlations by the DCC and DCCX model. Furthermore, in the DCCX model, it includes CBOE Volatility Index as the measurement of financial market uncertainty, analyzing whether it is associate with credit correlations.

The main results of our investigation into the behavior of credit spread correlations between sovereign debts as well as determinants can be summarized as follows. First, the credit spreads show time-varying characteristics and volatility cluster evidences. From estimation of DCC model, the dynamic correlations are significant and vary over time. The results are consistent with findings from unconditional estimation and also the results of Baig and Goldfajn (1999). Evidence shows that there is a close connection of credit quality among Asian countries and among those with the US. Second, the results of DCCX model indicate that correlations vary positively with VIX, that is, the correlation increases during the period when financial market uncertainty rises. Based on our results, investors could modify their estimation of correlations by investigating the variation of VIX. Third, in application of our finding, average correlation of volatility and correlation for underlying countries will be lower if we consider financial market uncertainty into the estimation of credit correlations. The other application is it helps investors to construct portfolio and provides a management strategy.

Our paper results contribute to understanding the time-varying correlation of credit risk. Overall, the main results of this paper could be beneficial from preventing asset value loss on one side and from well diversifying risk of portfolio on the other side. Our investigation can be refined by further exploring other exogenous variables for better explanation of dynamic correlations. For example, macroeconomic variables such as GDP growth and inflation are worth investigating. It also remains to be investigating whether other regions such us Latin America can provide further evidence of our consequence.

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Table 1

Descriptive Statistics

This table reports the summary statistics of credit spreads measured by 10-year sovereign bond yield of the US and five Asia countries - Japan, Hong Kong, South Korea (henceforth Korea), Thailand, and Taiwan – relative to US 1-year treasury yield. , respectively, in Panel A. All data are extracted from DataStream and the sample period is from November 1, 2000 to February 20, 2008. The series reported below are taking first-difference after calculation credit spreads. Std. Dev. refers to standard deviation. ρ_i is the i_{th} autocorrelation. Panel B reports the pair-wise unconditional correlations between two countries' credit spread change and between credit spread and CBOE VIX index. Here, the VIX is the natural log of the CBOE VIX.

Panel A: Sample moments

	Japan	Hong Kong	Korea	Thailand	Taiwan	US
Mean	0.009	-0.001	0.002	0.003	0.001	0.005
Median	0.004	-0.006	-0.005	0.000	-0.004	-0.004
Maximum	0.677	0.677	0.920	0.697	0.570	0.400
Minimum	-0.405	-0.407	-0.605	-0.338	-0.824	-0.215
Std. Dev.	0.140	0.146	0.181	0.141	0.170	0.076
Skewness	0.534	0.475	0.741	0.578	-0.131	0.827
Kurtosis	5.056	5.036	6.274	4.732	5.404	5.472
Jarque-Bera	85.435	80.336	205.609	69.021	93.093	140.837
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 1

(Continued)

	Japan	Hong Kong	Korea	Thailand	Taiwan	US
$\rho 1$	-0.086	-0.178	-0.065	-0.075	-0.021	-0.021
ρ_2	0.053	-0.014	0.005	0.029	0.008	0.100
ρ_3	0.003	0.027	0.034	-0.077	-0.080	0.022
ρ_{10}	0.034	0.017	0.001	0.080	0.067	0.008

Panel B: Correlation Matrix

	Japan	Hong Kong	Korea	Taiwan	Thailand	US
Hong Kong	0.445					
Korea	0.555	0.458				
Taiwan	0.754	0.424	0.513			
Thailand	0.589	0.366	0.490	0.551		
US	0.398	0.535	0.310	0.390	0.329	
VIX	0.235	0.150	0.185	0.183	0.109	0.279

Table 2

Two Stage Estimation of the DCC and DCCX Model

Stage 1 of DCC and DCCX estimations:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \varepsilon_{i,t} \left| \mathrm{I}_{t-1} : N(0, h_{i,t}), i = 1, 2, \ldots, 6 \right.$$

Stage 2 of DCC estimation:

$$\begin{bmatrix} q_{ii,t} & q_{ij,t} \\ q_{ji,t} & q_{jj,t} \end{bmatrix} = (1\text{-a-b}) \begin{bmatrix} 1 & \bar{q}_{ij} \\ \bar{q}_{ij} & 1 \end{bmatrix} + a \begin{bmatrix} z_{i,t-1}^2 & z_{i,t-1} z_{j,t-1} \\ z_{j,t-1} z_{i,t-1} & z_{j,t-1}^2 \end{bmatrix} + b \begin{bmatrix} q_{ii,t-1} & q_{ij,t-1} \\ q_{ij,t-1} & q_{jj,t-1} \end{bmatrix}, i,j = 1,2,\cdots,6$$

Stage 2 of DCCX estimation:

$$\begin{bmatrix} q_{ii,t} & q_{ij,t} \\ q_{ji,t} & q_{jj,t} \end{bmatrix} = (1\text{-a-b}) \begin{bmatrix} 1 & \bar{q}_{ij} \\ \bar{q}_{ij} & 1 \end{bmatrix} - \begin{bmatrix} 0 & c\bar{x} \\ c\bar{x} & 0 \end{bmatrix} + a \begin{bmatrix} z_{i,t-1}^2 & z_{i,t-1} z_{j,t-1} \\ z_{j,t-1} z_{i,t-1} & z_{j,t-1}^2 \end{bmatrix} + b \begin{bmatrix} q_{ij,t-1} & q_{ij,t-1} \\ q_{ij,t-1} & q_{jj,t-1} \end{bmatrix} + c \begin{bmatrix} 0 & x_{t-1} \\ x_{t-1} & 0 \end{bmatrix}, i,j = 1,2,\cdots,6$$

In the first stage, univariate volatility models are fitted to each time series for obtaining the volatility and residuals for each of six credit spread series of countries. In the second stage, residuals, transformed by their standard deviation estimated during the first stage, and $\bar{q}_{12} = E(z_{1,t}, z_{2,t})$ are used to estimate the parameter of the conditional correlation. By $q_{12} / \sqrt{q_{11,t} q_{22,t}}$, the conditional correlation is obtained. The variable ($\chi_{1,t-1}$) including in the formula is lagged natural log of VIX. The table shows estimations of two models using the MLE method. Numbers in the parentheses are t-value.

Panel A: Stage 1 of DCC estimation			
	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$
Japan	0.001	0.201	0.748
	(1.972)	(2.732)	(9.753)
Hong Kong	0.000	0.084	0.903
	(1.210)	(3.158)	(27.642)

Table 2

(Continued)

	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$
Korea	0.001	0.130	0.842
	(1.383)	(2.445)	(14.276)
Taiwan	0.000	0.071	0.918
	(1.162)	(2.231)	(23.952)
Thailand	0.002	0.130	0.803
	(1.755)	(2.408)	(9.613)
US	0.002	0.398	0.690
	(2.654)	(2.382)	(2.411)

Pane B: Stage 2 of DCC and DCCX estimation

	DCC		DCCX		
	$\hat{a}$	$\hat{b}$	$\hat{a}$	$\hat{b}$	$\hat{c}$
Japan-HK	0.029	0.886	0.032	0.846	0.186
	(1.223)	(7.590)	(1.276)	(6.927)	(1.980)
Japan-Korea	0.045	0.868	0.052	0.856	0.135
	(2.161)	(11.318)	(2.342)	(11.301)	(2.547)
Japan-Taiwan	0.085	0.859	0.072	0.880	0.103
	(3.405)	(19.931)	(2.953)	(23.021)	(3.476)
Japan-Thailand	0.146	0.678	0.145	0.681	0.039
	(4.015)	(7.722)	(3.963)	(7.414)	(2.322)
Japan-US	0.031	0.949	0.031	0.912	0.204
	(2.302)	(32.636)	(1.742)	(22.227)	(2.956)

Table 2

(Continued)

	DCC		DCCX		
	$\hat{a}$	$\hat{b}$	$\hat{a}$	$\hat{b}$	$\hat{c}$
HK-Korea	0.066	0.782	0.062	0.796	0.094
	(2.093)	(5.570)	(1.965)	(5.596)	(3.463)
HK-Taiwan	0.047	0.734	0.041	0.718	0.245
	(1.094)	(2.474)	(1.004)	(2.718)	(2.602)
HK-Thailand	0.024	0.933	0.035	0.831	0.142
	(1.565)	(12.260)	(0.880)	(6.064)	(3.204)
HK-US	0.077	0.625	0.074	0.669	0.058
	(1.622)	(1.941)	(1.557)	(1.968)	(0.316)
Korea-Taiwan	0.044	0.872	0.043	0.877	0.083
	(1.874)	(10.648)	(1.832)	(10.814)	(0.499)
Korea-Thailand	0.096	0.768	0.096	0.768	0.003
	(2.519)	(9.442)	(2.466)	(9.195)	(0.019)
Korea-US	0.036	0.915	0.045	0.825	0.246
	(1.649)	(13.096)	(1.697)	(10.380)	(4.463)
Taiwan-Thailand	0.077	0.833	0.08	0.792	0.189
	(3.044)	(11.486)	(2.844)	(8.817)	(3.656)
Taiwan-US	0.026	0.951	0.049	0.836	0.257
	(1.405)	(18.537)	(2.425)	(13.958)	(3.916)
Thailand-US	0.020	0.957	0.012	0.940	0.132
	(1.428)	(21.560)	(0.969)	(22.322)	(2.917)

Table 3

Investigation of Credit spread Correlations by Regressions

This Table reports the estimation of the regression below :

$$corr_{i,j,t} = a_0 + a_1 corr_{i,j,t\text{-}1} + a_2 \ln(vix_{t\text{-}1}) + v_t$$

$corr_{i,j,t}$ and $corr_{i,j,t-1}$ are conditional dynamic correlation of pair-wise credit spread correlation between two countries estimated by DCC model at time t and t-1. $\ln(vix_{t\text{-}1})$ is the natural log of the CBOE's VIX at time t-1. The regression is estimated by OLS and T-statistics are in parentheses,

	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_2$	Adj.R^2 (%)
Japan-HK	0.033	0.924	0.004	84.25
	(3.878)	(46.121)	(2.512)	
Japan-Korea	0.050	0.907	0.043	81.68
	(4.100)	(42.531)	(2.511)	
Japan-Taiwan	0.061	0.916	0.006	83.48
	(3.348)	(38.854)	(0.301)	
Japan-Thailand	0.126	0.780	0.012	90.34
	(5.879)	(23.169)	(2.430)	
Japan-US	0.006	0.984	0.008	95.87
	(1.451)	(93.744)	(1.794)	
HK-Korea	0.059	0.866	0.040	74.43
	(4.374)	(30.884)	(1.898)	
HK-Taiwan	0.128	0.694	0.003	87.75
	(9.563)	(22.127)	(0.193)	

Table 3

(Continued)

	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_2$	Adj.R^2 (%)
HK-Thailand	0.011	0.969	0.006*	92.72
	(2.304)	(68.406)	(1.909)	
HK-US	0.256	0.516	0.021	86.18
	(11.174)	(12.267)	(2.110)	
Korea-Taiwan	0.040	0.920	0.031	83.77
	(4.500)	(55.857)	(3.241)	
Korea-Thailand	0.070	0.850	0.052	71.48
	(5.125)	(33.342)	(2.007)	
Korea-US	0.013	0.958	0.034	91.18
	(2.843)	(70.699)	(2.965)	
Taiwan-Thailand	0.058	0.892	0.024	78.68
	(4.619)	(42.269)	(2.038)	
Taiwan-US	0.009	0.977	0.009	93.69
	(2.018)	(83.846)	(1.964)	
Thailand-US	0.005	0.984	0.018	95.51
	(1.663)	(95.566)	(2.282)	

Table 4

Average correlation between volatility and correlation

This table reports the average correlation (φ_i) of country *i*'s credit spread variance (h_{it}) with all its associated pair-wise correlation with other countries (ρ_{ijt}) as follows:

$$\varphi_i = \frac{1}{k-1}\sum_{j=1, i\neq j}^{k} \frac{\sum_{t=1}^{T}(h_{it}-\bar{h}_i)(\rho_{ijt}-\bar{\rho}_{ij})}{\sqrt{\sum_{t=1}^{T}(h_{it}-\bar{h}_i)^2\sum_{t=1}^{T}(\rho_{ijt}-\bar{\rho}_{ij})^2}}, i, j = 1, 2, \cdots, 6, i \neq j$$

In the left column of this table, it contains the average correlation between asset i's conditional variance and correlation without considering exogenous variable $\ln(vix_{t-1})$. The right column contains the average correlation between *i*'s conditional variance and correlation with considering variable $\ln(vix_{t-1})$.

Japan	0.423	0.384
Hong Kong	0.463	0.335
Korea	0.254	0.204
Thailand	0.406	0.289
Taiwan	0.265	0.207
US	0.395	0.378
average	0.368	0.300

Table 5

The minimum-variance portfolio of Asia and US debts

This table reports the weights of two assets in a minimum-variance portfolio. The weights of two assets are estimated by follows:

$$\text{Min} \quad h_t = w_{a,t}^2 h_{a,t} + w_{u,t}^2 h_{u,t} + 2 w_{a,t} w_{u,t} \sqrt{h_{u,t} h_{a,t}} \rho_t$$

$$w_{a,t} = \frac{h_{u,t} - \sqrt{h_{u,t} h_{a,t}} \rho_t}{h_{a,t} + h_{u,t} - 2\sqrt{h_{u,t} h_{a,t}} \rho_t}$$

$$w_{u,t} = 1 - w_{a,t}$$

$$w_{a,t} = \alpha + \beta \ln(vix_{t-1}) + \varepsilon_t$$

$$w_{u,t} = \alpha + \beta \ln(vix_{t-1}) + \varepsilon_t$$

w_a and w_u are weights for Asian and the US debts, respectively. h_t is the covariance of the portfolio. ρ_t is the conditional correlation considering $\ln(vix_{t-1})$ between Asian and the US sovereign debts.

	$\hat{\alpha}$	$\hat{\beta}$	Adj.R^2 (%)
Wa	0.306	-0.076	79
Wu	0.694	0.076	79

Panel A: credit spreads

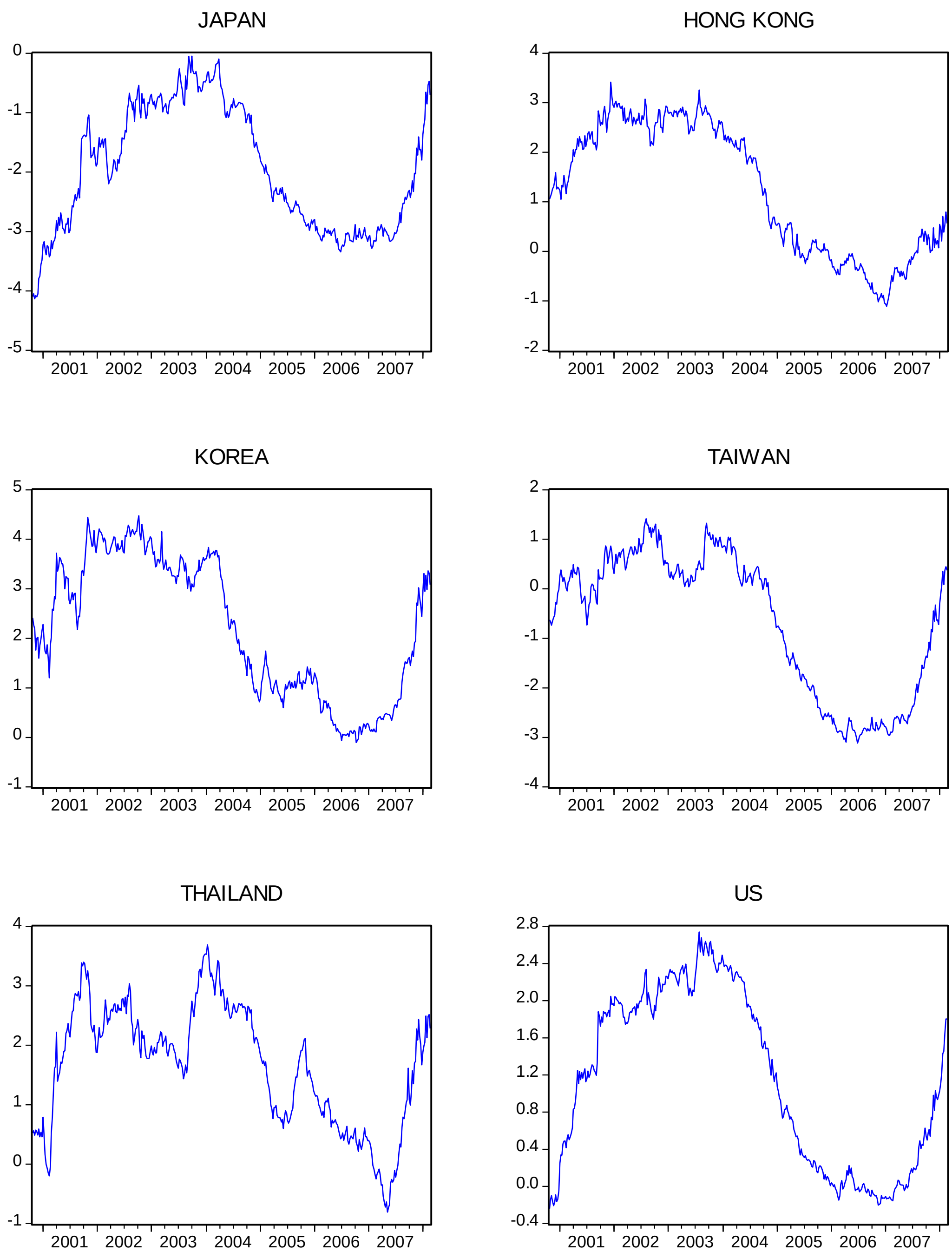


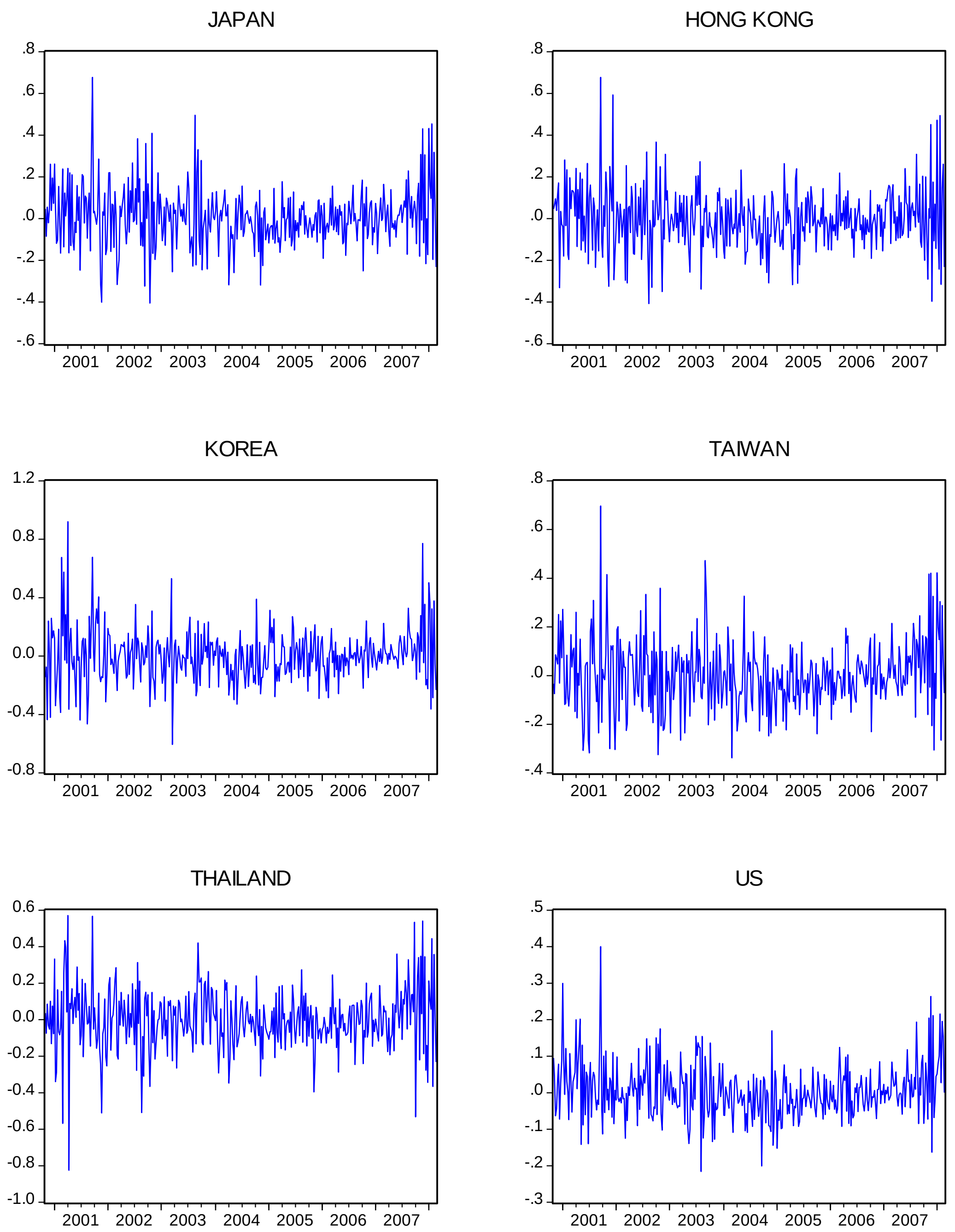
Figure 1 Credit spreads and changes of five Asia countries and US.

The credit spreads are 10-year bond yields relative to the US treasury yield.

Figure 1

(Continued)

Panel B: credit spreads changes



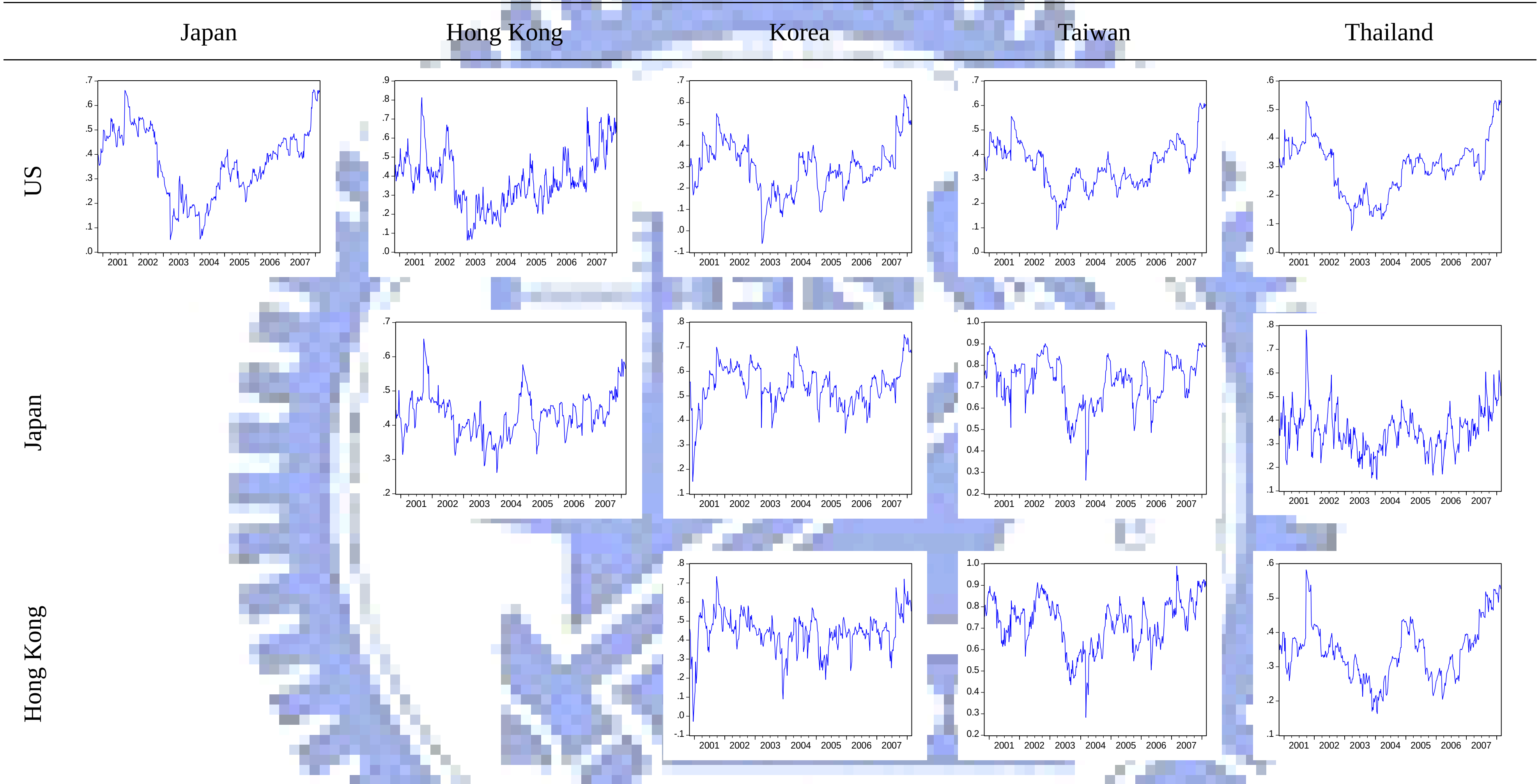
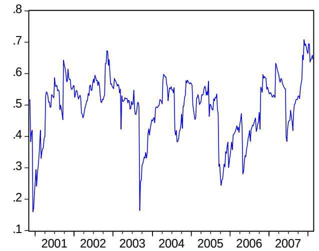
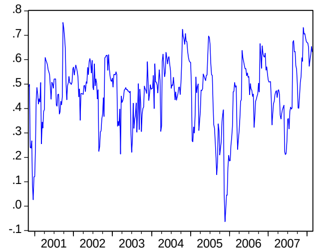
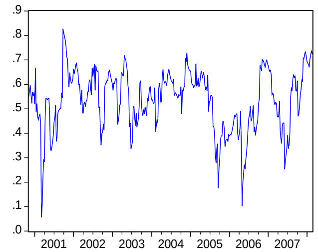


Figure 2 Credit spread correlations with the DCCX model

This figure displays the time-series of dynamic conditional correlations between credit spreads estimated by the DCCX model.

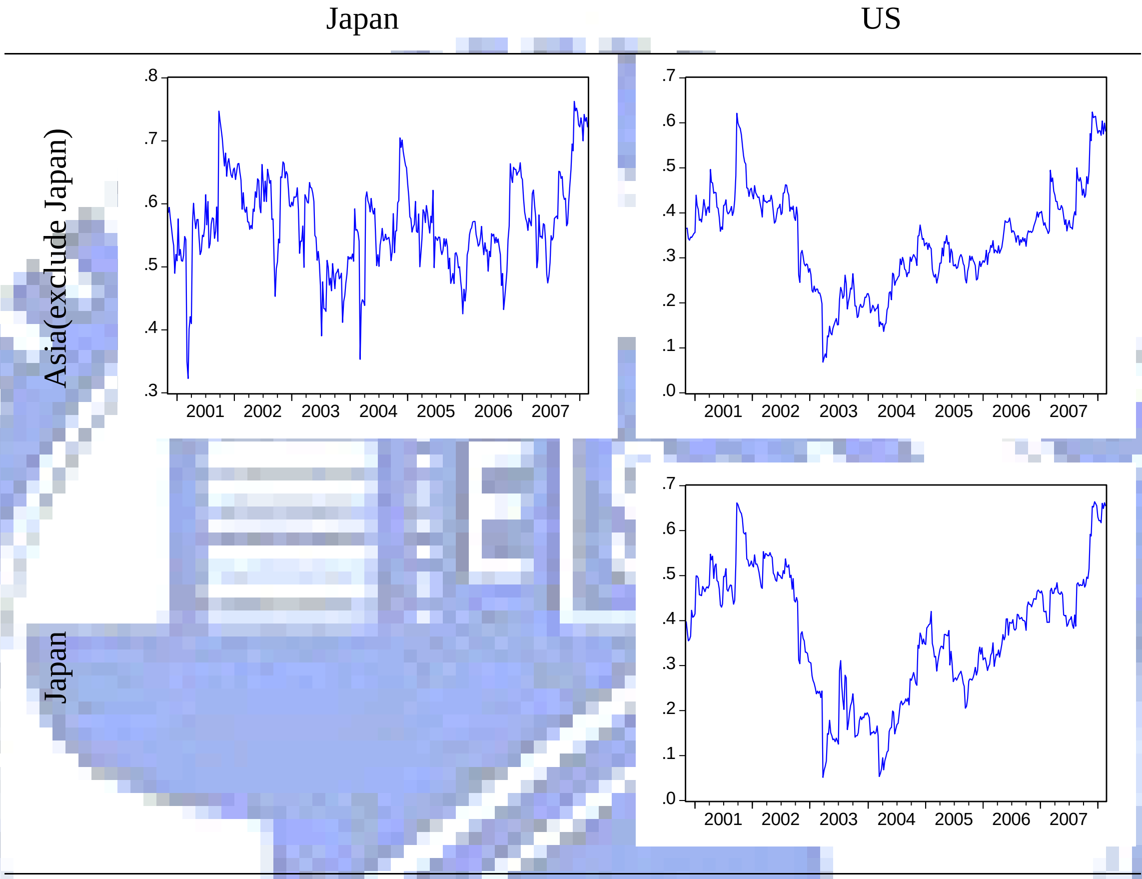
Figure 2

(Continued)

	Japan	Hong Kong	Korea	Taiwan	Thailand
Korea					
Taiwan					

Panel A: average correlation between

Asia countries (exclude Japan), Japan, and US



Panel B: average correlation between all countries

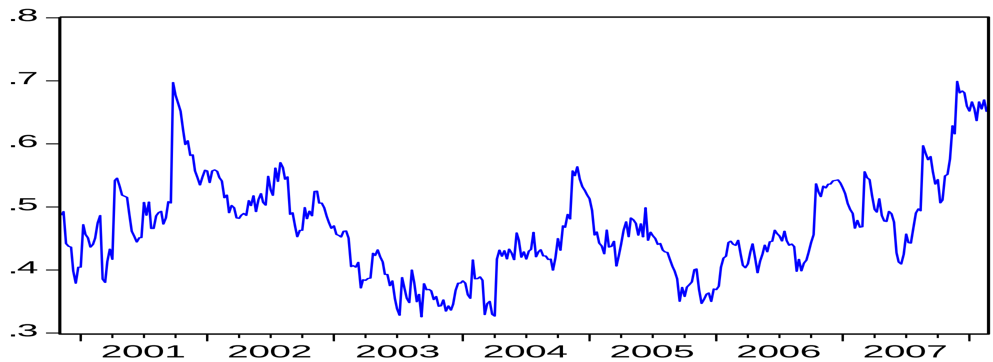


Figure 3 Average credit spreads correlation with the DCCX model

Panel A represents average correlation between three markets- US, Asia countries (exclude Japan) and Japan. Panel B represents average correlation among six countries. Panel C is the figure of VIX.

Figure 3

(Continued)

Panel C: Natural Log of CBOE VIX