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Integration of China Stock Markets with International Stock Markets: An Application of Smooth Transition Conditional Correlation with Double Transition Functions*

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Abstract

This paper employs STCC-GARCH and DSTCC-GARCH models to investigate the time varying return co-movements between Chinese stock markets and stock markets of the US, UK, France and Japan. Unlike the earlier literature, we uncover that there are noticeable rising trends in conditional correlations among these markets particularly following the financial reforms in China. Moreover, the empirical results of DSTCC-GARCH specifications with time and various volatility measures indicate that the correlations increase not only over time but also during calm periods for A-shares, though mixed results are obtained for B-shares.

JEL Classification: C32, C58, F36, G15

Keywords: Multivariate GARCH, Smooth Transition Conditional Correlation, Stock Markets Integration and Co-movements.

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1. Introduction

Last three decades have witnessed immense developments in information technology, establishment of multinational companies and liberalization of financial systems and capital markets which in turn led to the simultaneous high price changes and integrations both in domestic and international financial markets. However, although financial assets within a market and financial markets within an economy have become more dependent, the full integration of international markets has not yet been fully completed partially due to differences in levels and structure of economic growth and timing of business cycles among countries. Hence, as Solnik (1974) points out international diversification may still provide opportunities to reduce portfolio risk.

The information regarding the structure and properties of correlations among international financial markets is essential to evaluate the potential benefits of international portfolio diversification. This fact has motivated many scholars to examine the return correlations across international markets using time varying correlation models within the multivariate GARCH framework. The main focus in the recent literature has been to reveal the expected upward trend in the correlation and nature of dynamic co-movements. However, although liberalization in the financial markets has started in as early as 1980s, the mixed results of earlier empirical studies do not allow an agreement on expected increasing trend in co-movements among financial markets up to 2000s. King et al. (1994), Longin and Solnik (1995), and Ramchand and Susmel (1998) establish that the correlations among financial markets have a time varying nature and tend to increase mostly during high volatile times. Longin and Solnik (2001), and Ang and Bekaert (2002), on the other hand, report that the reaction of correlations to the volatility is asymmetric and correlations increase during high volatile bear markets.

After 2000, the findings in the literature imply that the correlations among financial markets have shown increasing trend over time, particularly being more apparent among developed countries and among countries in the same region. Cappiello et al. (2006), for instance, report that the level of correlation varies from country to country and from region to region, but the highest levels are observed among developed countries in European Union (EU). Using weekly data from January 8, 1987 to February 7, 2002 and an asymmetric and generalized version of Dynamic Conditional Correlation[2] GARCH (DCC-GARCH) model of Engle (2002), they investigate the correlation structure of 21 countries' stock and bond markets from Europe, America and Australasia[3]. Empirical results show increasing trend in correlation among financial markets mainly in Europe and a structural break in correlations in January 1999 which coincides with the introduction of Euro as a single currency. It is also noted that the correlations among Australasian group, Americas, and Europe seem to be unaffected from the developments in Euro area. It is argued that the depreciation of the euro vs. the US dollar right after the introduction of euro may be due to increase in correlation among stock markets of EMS member countries which led investors to diversify their portfolios less on EU countries and more on the US leading capital movement from Europe to the US due to new portfolio weights adjusted to the changes in correlation. Unlike Cappiello et al (2006), Kim et al.

[2] The original DCC-GARCH model of Engle (2002) defines scalar coefficients for conditional correlation equation. Therefore country specific news impact and smoothing parameters are not allowed in this model.

[3] Countries in European are Austria, Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and UK, in Australasia are Australia, Hong Kong, Japan, New Zealand, and Singapore, and in Americas are Canada, Mexico, and the US.

(2005) employ bivariate EGARCH model with time varying conditional correlation to describe daily data of stock markets in EMS countries, Japan and the US for the period from January, 1989 to May, 2003 and find that upward trend in correlation is valid for all international markets since the introduction of Euro. Similar conclusions are obtained in Savva et al. (2009) using multivariate DCC-GARCH model for daily data of indices in UK, Germany, France and the US for the period from December, 1990 to August 2004. Compared to Cappiello et al (2006) the longer and high frequency samples in the last two papers seem to allow capturing the effects of single currency on the correlation between the Euro and non-Euro area.

Silvennoinen and Teräsvirta (2009) use smooth transition conditional correlation (STCC) model within the MGARCH framework to examine the properties of conditional correlations among DAX index in Germany, CAC40 index in France, FTSE index in UK and HSI index in Hong Kong with weekly data for the period from the first week of December 1990 to the last week of April 2006. It is found that the correlations among these stock market indices increase to higher levels in the spring of 1999, CAC-DAX, CAC-FTSE and DAX-FTSE exceed 0.9, 0.85 and 0.8 respectively. They also reveal that the increasing conditional correlations among stock markets in European countries are affected by the level of volatility since 1999. In a similar work, Aslanidis et al. (2010) analyze the correlation structure between S&P500 and FTSE indices and find that increasing trend in conditional correlation reaches to 0.9 around February 2000 and although volatility plays a crucial role before 2000 it loses its significance since then.

To conclude, recent literature reveals that the correlations among financial markets of developed countries are very high and leave little room for international portfolio diversification. This in turn suggests that investors should look for an emerging market whose correlations with international financial markets are low (or even negative) and which have potential to grow fast. A popular alternative is China as it offers huge opportunities in all areas of economy to investors due to its large economic scale and impressive economic growth. Despite the global financial turmoil since 2008, Chinese economy has achieved to keep growing at quite high rates compared to many developing and developed economies.

China's two securities markets, the Shanghai Securities Exchange and the Shenzhen Stock Exchange, were established on December 19, 1990 and July 3, 1991, respectively. The shares initially listed on these exchanges are called A-shares, and they could only be traded by Chinese citizens and denominated in Renminbi. In 1992, another category of shares, B-shares, was introduced for foreign investors and although they are denominated in Renminbi, traded in foreign currency. All transactions and dividend payments of B-shares are in US dollars in Shanghai and Hong Kong dollars in Shenzhen. The number of listed companies has grown very rapidly from 53 to 894 since 1992. At the end of 2010, Shanghai Stock Exchange has been the world's 5th largest stock market by market capitalization which is about US$2.7 trillion.

China has initiated several structural reforms and liberalization policies since 1999 with the introduction of security law. In 2001 domestic investors started to trade B-shares. Following the introduction of qualified foreign institutional investor program which has relaxed the restriction on A-shares, qualified foreign investors started to trade A-shares in July, 2003. Since May 2006, qualified domestic institutional investors were allowed to invest in foreign developed stock markets. These two programs were due to commitment of China to liberalize its financial markets during its admission to the World Trade Organization (WTO) in December, 2001. Besides, China also committed itself to list its large state-owned enterprises on foreign stock markets and let foreign enterprises be listed on the stock markets in China. However these two policy actions took place at the end of 2006. With these structural reforms, China seems to be dedicated to become one of the largest world economies and to rapidly integrate with the rest of the world economies.

Although following these reforms and economic integration of China with the rest of the world, a significant increase in the correlation of Chinese stock markets with developed financial markets is expected, empirical applications do not seem to be providing evidences in favor of these expectations so far. Li (2007) uses BEKK specification to examine the linkages between China and the US stock markets for daily data from January, 2000 to August, 2005 and finds no direct volatility spillover between the US and China stock markets. Moreover, Lin et al. (2009) employ DCC-GARCH model to analyze dependency among China and world markets and do not find evidence of an increasing trend. Moon and Yu (2010) argue that the poor results of both papers in favor of rising trend may be due to short samples excluding the period in which the effects of structural reforms and liberalization policies has been realized in the financial markets of China. Moon and Yu (2010) do not identify an increasing trend in their paper analyzing daily return rates of stock markets in China and in the US from January, 1999 to June, 2007, but they are able to detect a structural break at end of 2005 and report symmetric and asymmetric volatility spillover effects from the US to China stock markets and symmetric volatility spillover effect from China to the US since this date.

This paper investigates the dynamic structure of weekly return correlations among Chinese stock markets (A-share and B-share indices) and stock markets in four developed countries, namely the US, UK, France and Japan. To incorporate well established dynamic structure of the conditional correlations among international stock markets, we opt for multivariate GARCH (MGARCH) models with time varying conditional correlations by using smooth transition conditional correlation (STCC-GARCH) and double smooth transition conditional correlation (DSTCC-GARCH) specifications proposed by Silvennoinen and Teräsvirta (2005 and 2009).

We first seek for an evidence of increasing trend in the conditional correlation among Chinese stock markets and stock markets in the US, UK, France and Japan using calendar time as a transition variable in STCC-GARCH model. Besides, we investigate how conditional correlation is affected by global volatility, market specific volatility and the sign of the news from markets by considering various measures of these factors as candidate transition variable in STCC-GARCH and DSTCC-GARCH parameterizations. Empirical results are in line with our expectations indicating rising trends as far as correlation of developed stock markets with Chinese markets are concerned. Furthermore, the results imply that the correlation structure is highly affected by market volatility with volatile periods leading lower correlations compared to the more tranquil periods for A-share index but the results are mixed for B-share index.

The plan of the paper is as follows. Next section introduces the models and estimation details. Section 3 discusses the data set used and presents the estimation results. Finally, last section concludes the paper.

2. Econometric Models and Estimation

To capture the time varying nature of return correlations, Silvennoinen and Teräsvirta (2005 and 2009) define conditional correlation as a function of observable variable(s) in STCC-GARCH and DSTCC-GARCH models. In the former model, two regime-specific constant correlations and in the latter one four regime-specific constant correlations are defined. The conditional correlations are allowed to change smoothly between these extreme correlation regimes over time with respect to the value of an observable transition variable in STCC-GARCH and two observable transition variables in DSTCC-GARCH specification. The choice of the transition variable depends on the purpose of application and theoretically, any variable can be a candidate for transition variable allowing very high flexibility in terms of variable selection for conditional correlation equation. Silvennoinen and Teräsvirta (2005 and 2009) propose test procedures to check whether the variables of interest are capable of representing the factors which determines the dynamic structure of the conditional correlation. Hence, in line with our aim, these models not only can characterize increasing trend by using calendar time as a transition variable but also able to uncover the structure and properties of the correlation structure in response to the measures of global volatility, market specific volatility and the type of the news from markets.

Unlike widely used DCC-GARCH model of Engle (2002), these models allow interaction between GARCH processes and conditional correlation equations by simultaneous estimation instead of two-step estimation. Besides, these models, by defining smooth transition between extreme regimes, are capable of incorporating the possibility of heterogeneous agents responding to developments at different times. And also in this framework any structural change through time or with respect to particular transition variable can be detected without ex ante information of change.

The relevant equations and modeling procedure can be given as follows. The mean equations of stock returns for a 2-dimensional stochastic vector of stock returns is

$$y_t = E(y_t|\Theta_{t-1}) + u_t \qquad t = 1,2, \ldots T \tag{1}$$

$$y_t = \left[y_{i,t}, y_{j,t}\right]' \tag{2}$$

where i = Shgh-A and Shgh-B
j= S&P500, FTSE, CAC, Nikkei

The mean equation (1) for each stock market index is formulated as an autoregressive AR (L_k) process with different lag length in order to eliminate the linear dependence in the standardized errors.

$$y_{k,t} = \mu_k + \sum_{l=1}^{L_k} \beta_{kl} y_{k,t-l} + u_{k,t} \qquad k = i,j$$

Θ_{t-1} contains all available information up to time *t-1*. The conditional covariance of the shocks in equation (1) are time-varying, such that

$$u_t \mid \Theta_{t-1} \sim (0, H_t) \tag{3}$$

Instead of defining H_t directly, by following Bollerslev (1990), it is decomposed as

$$H_t = D_t R_t D_t \tag{4}$$

where D_t is a 2×2 diagonal matrix whose diagonal elements are square root of conditional variances (i.e. $\sqrt{h_{i,t}}$ and $\sqrt{h_{j,t}}$) and R_t is a symmetric conditional correlation matrix whose diagonal elements are unity and off-diagonal elements are between -1 and 1. Dynamics for elements of D_t are defined with imposing the non-negativity and stationarity restrictions and each element can follow different GARCH processes. Since the performance of GARCH (1,1) model is sufficient to represent dynamics of financial time series, each element of D_t, i.e. each variance, is modeled as GARCH(1,1) process separately[4]. Therefore, in this way conditional covariance matrix is defined indirectly and its conditional covariance elements are represented by product of conditional correlation and square root of conditional variances.

$$h_{i,t} = \alpha_{0i} + \alpha_{1i} u_{i,t-1}^2 + \alpha_{2i} h_{i,t-1} \tag{5}$$

$$h_{ij,t} = \rho_t (h_{i,t} h_{j,t})^{1/2} \tag{6}$$

Silvennoinen and Teräsvirta (2005), assume that R_t, is governed by two extreme regimes and the conditional correlation changes smoothly between them, i.e.

$$R_t = P_1\big(1 - G_t(s_t; \gamma, c)\big) + P_2 G_t(s_t; \gamma, c) \tag{7}$$

Where P_1 and P_2 are regime specific constant correlation matrices whose diagonal entries must be unity and off-diagonal elements must be less than or equal to unity in absolute value as in regular correlation matrix. However unlike DCC-GARCH model[5], this is not guaranteed by construction. The elements of P_1 and P_2 are parameters to be estimated and needs to be controlled during the estimation.

In equation (7), $G_t(s_t; \gamma, c)$ is the transition function of an observable transition variable, s_t, and bounded between zero and unity. When $G_t(.)$ equals to zero the conditional correlation is governed by only P_1 and the conditional correlation is in the first regime. Similarly, when it takes on the value of one the conditional correlation equals to P_2 and it is in the second regime. These extremes ($G_t = 0$ and $G_t = 1$) may be associated with distinct regimes, such as low and high correlation regimes. The other values of the transition function correspond to transition between extreme regimes and during transition, the conditional

[4] For Shgh-B, GARCH(3,1) eliminates the dependence in squared standardized errors.

[5] In DCC model, a GARCH type dynamic for conditional correlation, R_t, is not directly defined. Instead, a GARCH process is defined for Q_t, and R_t is defined by Q_t in a manner which guarantees that R_t become a regular correlation matrix whose diagonal entries must be unity and off-diagonal elements must be less than or equal to unity.

$$Q_t = (1 - a - b)\bar{Q} + aZ_{t-1}Z'_{t-1} + bQ_{t-1} \tag{I}$$

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

where Q_t* is a diagonal matrix whose diagonal entries are square root of the diagonal elements of Q_t, and $\bar{Q}$ is the unconditional covariance matrix of the standardized residuals.

correlation (R_t) is a convex combination of P_1 and P_2. The proper choice of transition function is the logistic one

$$G_t = (1 + e^{-\gamma(s_t - c)})^{-1} \qquad \gamma > 0 \tag{8}$$

This function is characterized by slope parameter γ indicating the smoothness of transition and by location (threshold) parameter c showing the half-way point between two regimes. As the logistic function is monotonically increasing from zero to unity and R_t is a linear combination of P_1 and P_2, it describes a monotonic transition from P_1 to P_2 as (s_t - c) increases.

A special case of the STCC model uses scaled calendar time as the transition variable, $s_t = t / T$, which gives rise to the time-varying conditional correlation model of Berben and Jansen (2005). This allows a smooth change between correlation regimes and as $\gamma \rightarrow \infty$ model captures a structural break in the correlations. This transition variable may be particularly relevant in order to capture the effects of increasing integration of financial markets as in our case.

Silvennoinen and Teräsvirta (2009) generalize equation (7) to DSTCC-GARCH model to allow for two transition functions with two distinct transition variables by relaxing the assumption that P_1 and P_2 are regime specific constant correlation and define R_t as a function of $P_{1,t}$ and $P_{2,t}$.

$$R_t = P_{1,t}\left(1 - G_{1,t}(s_{1,t}; \gamma_1, c_1)\right) + P_{2,t}G_{1,t}(s_{1,t}; \gamma_1, c_1) \tag{9}$$

Which makes R_t a function of second transition function with respect to observable second transition variable with $P_{1,t}$ and $P_{2,t}$ taking values between (P_{11} and P_{12}), and (P_{21} and P_{22}) respectively.

$$P_{s,t} = P_{s1}\left(1 - G_{2,t}(s_{2,t}; \gamma_2, c_2)\right) + P_{s2}G_{2,t}(s_{2,t}; \gamma_2, c_2) \qquad s = 1,2 \tag{10}$$

When we substitute equation (10) in to equation (9), the conditional correlation equation becomes

$$R_t = (1 - G_{2,t})\left((1 - G_{1,t})P_{11} + G_{1,t}P_{21}\right) + G_{2,t}((1 - G_{1,t})P_{12} + G_{1,t}P_{22}) \tag{11}$$

where the transition functions $G_{1,t}$ $(s_{1,t}\ ;\ \gamma_1\ ,c_1)$ and $G_{2,t}$ $(s_{2,t}\ ;\ \gamma_2\ ,c_2)$ are logistic functions with different transition variables ($s_{1,t}$, $s_{2,t}$), location (c_1 , c_2), and slope parameters (γ_1, γ_2). P_{11}, P_{12}, P_{21} and P_{22} are regime specific constant correlation matrices. To be clearer, the first transition function describes two different regimes (P_1 and P_2) and the second one allows two distinct regimes within the each regime of the former one (i.e., $P_1 \rightarrow P_{11}$ and $P_{12};$ $P_2 \rightarrow P_{21}$ and P_{22}). Therefore in DSTCC-GARCH model the conditional correlation, R_t, is described by four regimes[6]. When the conditional correlation is in the first regime with respect to the second transition function (i.e. $G_{2,t} = 0$) R_t takes on values between P_{11} and P_{21} as a function of the first transition function, and during the second regime (when $G_{2,t} = 1$) it takes on values between P_{12} and P_{22} as a function of the first transition function. Hence, the system can move from

[6] If the transition variables are the same then conditional correlation is governed by three extreme regime specific correlations with two distinct transition functions, See Öcal and Osborn (2000).

P_{11} to P_{21} and P_{12} to P_{22} only by the dynamics of the first transition function in case of these extremes. Otherwise, the movements among four regimes are governed by both transition functions.

In this paper, we model conditional correlation between each one of the eight index pairs (Shgh-A – S&P500, Shgh-A – FTSE, Shgh-A – CAC and Shgh-A – Nikkei, and same pairs for Shgh-B), rather than analyzing all indices under one specification for the following reasons: modeling correlation matrix of a multivariate model with more than two variables in STCC-GARCH and DSTCC-GARCH framework implicitly impose the condition that the correlation between all pairs must be governed by not only the same transition variable with same lag, but also by the same threshold value and same slope parameter. As far as the former concerned, this requires the assumption that the correlations between, for example, Shgh-A – S&P500 and S&P500 – FTSE are governed by same transition variable which may not be realistic. Although it is possible to generalize these models with common transition variable but different slope and threshold parameters, this is quite impractical due to increasing number of parameters to be estimated and also the positive definiteness of correlation matrix may be difficult to retain as pointed out in Silvennoinen and Teräsvirta (2005 and 2009). Even if one manages to estimate a multivariate model with several transitions functions, the interpretation of parameters may not be an easy task and inferences on bivariate dynamics may not be clarified. As our results show in section 3.2, different transition variables for different index pairs govern the change from one correlation regime to other strengthening our view. In addition, transition dates do not seem to be matching, making a multivariate modeling impractical at least for the indices analyzed here.

Our modeling procedure basically follows the methodology suggested in Silvennoinen and Teräsvirta (2005, 2009) and can briefly be outlined as follows.

- Determine the candidate transition variables in modeling STCC-GARCH model. We consider four groups of variables that may be relevant factors in examining the nature of correlations among stock markets based on the findings of literature; the first group only includes calendar time to check the increasing trend hypothesis, the second group contains VIX index as a measure of global volatility, the third one consists of variables to measure index specific volatility (lagged conditional variance[7], lagged absolute error and lagged absolute standardized error[8], lagged squared error and lagged squared standardized errors) and the last group contains measures of the news from indices (lagged errors and lagged standardized error). To find the significant transition variables, all variables in each group and up to four lags of all variables in the last three groups are considered. Besides, variables derived for S&P500, HSI, and Nikkei indices are taken in to account for all pairs. This in turn produces 117 transition variables for S&P500 and Nikkei indices and 145 candidates for FTSE and CAC indices that should be tested both in single and double transition functions hypothesis.
- Conduct LM_1 test of Silvennoinen and Teräsvirta (2005) to test the null hypothesis of constant conditional correlation (CCC) against the alternative hypothesis of STCC-GARCH for each candidate transition variable. This step is essential to eliminate the possibility that the parameters

[7] Conditional variance series are generated by univariate GARCH(1,1) model for each index separately.

[8] Errors are from GARCH(1,1) model and standardized errors are generated by dividing errors to square root of conditional variance.

of the correlation equation in the STCC-GARCH model are not identified and its estimation may lead to inconsistent parameter estimates, if the true model has CCC structure

- Among significant transition variables, select the one providing the smallest *p*-value as the appropriate transition variable and estimate STCC-GARCH specification with this one. However, if the null hypothesis is rejected for more than one candidate transition variable with close *p*-values preventing a clear cut selection, then estimate STCC-GARCH with each of them and defer the selection of appropriate transition variable and/or model to post-estimation.

- Carry out LM_2 test of Silvennoinen and Teräsvirta (2009) to all estimated STCC-GARCH models to uncover whether a second transition function is needed. Here, we again consider all variables in the four groups. This in turn allows us not only to identify the second transition function but also to have an idea if the transition variable used in the estimation of STCC-GARCH model is the optimal one. It is worthy of note that the null hypothesis of STCC-GARCH model with the best transition variable can be rejected against the alternative DSTCC-GARCH models for various transition variables, in this case we again estimate DSTCC-GARCH model for all of them and leave model selection to post estimation.

- Estimate STCC-GARCH and DSTCC-GARCH models by maximum likelihood (ML) under the assumption of conditional normality of standardized errors.

$$z_t|\Theta_t \sim N(0, R_t) \tag{12}$$

where $z_t = D_t^{-1}u_t$ then the log-likelihood for observation t is

$$l_t = -\log(2\pi) - (1/2)\sum_{i=1}^{2}\log\big(h_{i,t}\big) - (1/2)log|R_t| - (1/2)z_t' R_t^{-1} z_t \tag{13}$$

and $\sum_{t=1}^{T} l_t$ is maximized with respect to model parameters.

Due to nonlinear fashion of the models and the large number of parameters, estimation of all equations (mean, conditional variance and correlation, and transition function) jointly at once is quite problematic. Moreover, initial values of parameters are very crucial in estimation and different initial values may lead to convergence to different parameter values which may correspond to local maxima. As an attempt to find the global maxima we perform grid search over the parameters of the transition functions. The initial values of parameters in mean, conditional variance and correlation equations are determined by following the iterative procedure suggested by Silvennoinen and Teräsvirta (2005) which divides the parameters into three sets: parameters in the mean and variance equations, correlations, and parameters of the transition function, and the log-likelihood is maximized by sequential iteration over each set by holding the parameters of other set at their previously estimated values. With these initial values, all equations are estimated simultaneously at once[9].

[9] All estimations are performed using RATS 8.0. Our own source code are adapted from the Ox code which is kindly supplied by Annastiina Silvennoinen.

The estimated models are first assessed for their ability to capture the conditional correlation dynamics via transition between regime specific constant correlations. At this point, the location of the estimated threshold value and the estimated correlation levels corresponding to each regime are very important. If the number of observations, above or below the estimated threshold value is very small and/or the difference between correlation regimes is insignificant, estimated STCC-GARCH and DSTCC-GARCH models are discarded. The best model, among the satisfactory ones, is selected according to maximum likelihood value, AIC and SIC statistics.

Since the interpretation of individual parameter estimates is not very informative due to large number of parameters, following the literature we prefer the graphs of estimated conditional correlations to discuss the estimation results.

3. Data and Empirical Results

3.1 Data

Daily closing price of Shanghai Securities Exchange A-shares index (Shgh-A) and B-shares index (Shgh-B), S&P500 index in the US, FTSE index in UK, CAC index in France, and Nikkei index in Japan are obtained from Global Financial Data. The daily price data is transformed to continuously compounding weekly returns by log-differencing[10] Thursday closing prices. The sample contains 1002 weekly observations[11] from December 20, 1990 to December 30, 2010 for Shgh-A and 938 weekly observations[12] from February 27, 1992 to December 30, 2010 for Shgh-B. We opt for weekly returns to alleviate the possible effects of different opening hours. An aggregation over time is expected to weaken these effects. The choice of Thursday closing price in calculating weekly return, instead of using end of week closing price, is an attempt to avoid any possible end-of-week effects. All indices are denominated in local currencies to exclude the possible effects of exchange rate volatility. The extremely positive returns which are outside the four standard deviations confidence interval around the mean are replaced by mean plus four standard deviation and the extreme negative returns are treated in the same way. This truncation is necessary for Shgh-A index in estimation of GARCH parameters. Otherwise, estimated GARCH parameters do not meet the positivity and stability conditions of GARCH process. This truncation also mitigates the effects of outliers on LM tests used in determining appropriate transition variables.

Figures 1 and 2 indicate the evolution of price and weekly return series of indices through time. Former Figure indicates that indices can be divided into three groups: indices in China, indices in west developed countries of the US, UK and France, and index in Japan. Before 2004, very similar dynamics are shared by the indices within each group. However after 2004 all indices share common trends: since 2004, they all started to increase and reached to their specific peaks in 2008 then decreasing trend dominates the all indices up to mid-2009 after which recovery phase seems to be started.

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[10] $R_{i,t} = (\log(P_{i,t}) - \log(P_{i,t-1})) \times 100$, where $P_{i,t}$ is the Thursday closing price of stock market i at time t.

[11] The period from December 20, 1990 to December 30, 2010 consists of 1046 weeks. 60 observations are missing for Shgh-A. 44 of them are deleted from the sample and 16 are replaced by the average value of previous and next week return rates.

[12] The period from February 27, 1992 to December 30, 2010 consists of 983 weeks. 59 observations are missing for Shgh-B. 45 of them are deleted from the sample and 14 are replaced by the average value of previous and next week return rates.

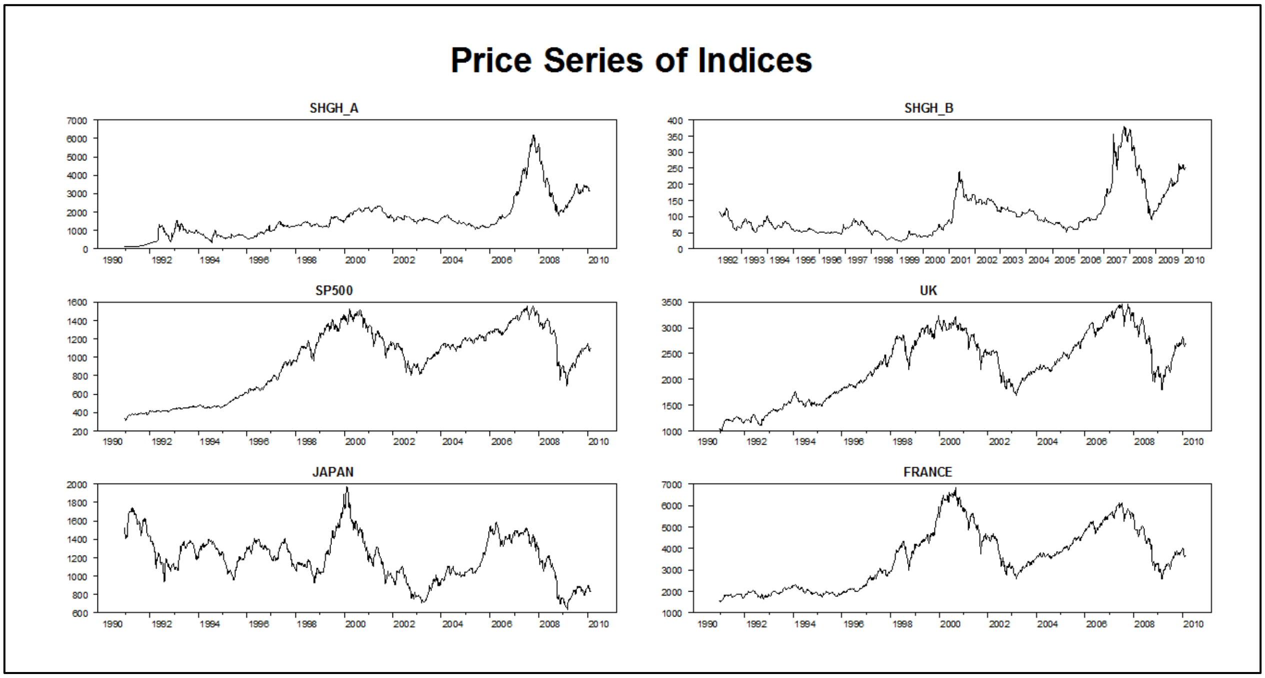

Figure 1: Weekly price series of Shgh-A, Shgh-B, S&P500, FTSE, Nikkei and CAC

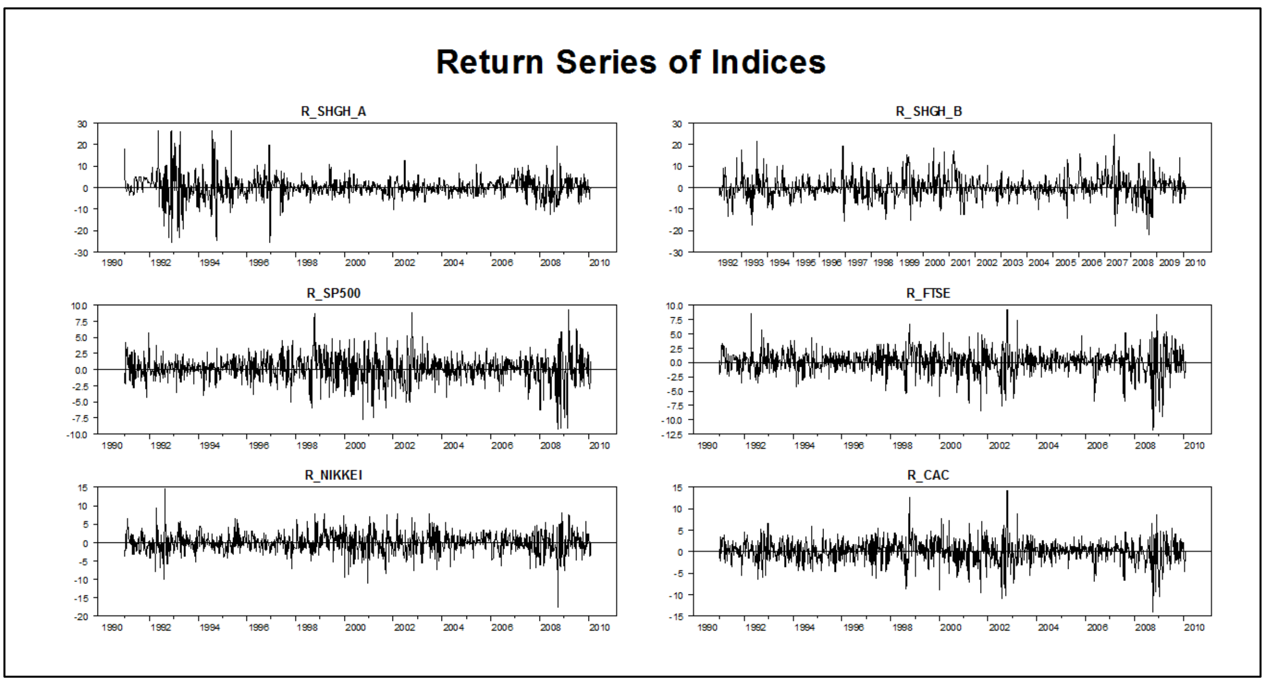

Figure 2: Weekly return series of Shgh-A, Shgh-B, S&P500, FTSE, Nikkei and CAC

As return series of indices in Figure 2 show, although low volatility is peculiar during rising trend period, high volatility dominates when the indices are in downward phase. The volatility is also at high levels during the years between 1997 and 2003 which coincides with the Asian and Russian financial crisis and internet companies' crash.

Table 1 summarizes the descriptive statistics of weekly return rates of indices. During the sample period, the better performance of Shgh-A index relative to other indices is quite apparent. Its mean return rate is 3 times higher than other indices'. An interesting feature revealed by this Table is that although identical shares are traded in both Shgh-A and Shgh-B, the mean return of Shgh-B is much lower than Shgh-A (it is in fact one third of Shgh-A) and it is also lower than mean return rates of S&P500. The possible reasons of this difference in Shgh-A and Shgh-B indices may be potential information advantage of domestic investors, the illiquidity of the B-share market and speculation premium for A-share markets[13].

	Mean	SD	Skewness	Kurtosis (excess)
Shgh-A	0.3317	6.3519	3.919	51.45
Shgh-B	0.1009	5.315	0.363	2.773
S&P500	0.1336	2.3709	-1.449	10.74
FTSE	0.109	2.2388	-0.6505	3.459
CAC	0.0907	2.847	-0.417	2.528
Nikkei	-0.056	2.8706	-0.242	2.6409

Table 1: Descriptive statistics of weekly return rates

The second stylized fact which is not surprising is that Shgh-A and Shgh-B indices' returns are more volatile. It is almost 2 times higher than average volatility of other indices. Except for Shgh-A and Shgh-B, all indices are left skewed which means that the majority of the return rates are higher than its mean probably due to limited number of, but larger, negative returns. On the other hand, the majority of the returns in Shgh-A and Shgh-B indices are less than their means and larger but limited number of positive returns raising the mean. Although high standard deviation of Shgh-A and Shgh-B share indices imply that these two indices are more risky than other indices, right skewness of Shgh-A and Shgh-B share indices imply that large negative returns are not as likely as large positive returns which means that these two indices are not more risky in terms of losses. The fat tail property of financial time series is also apparent from the excess kurtosis of all indices.

	Shgh-A	Shgh-B	S&P500
Shgh-B	0.5988	1	
S&P500	0.0293	0.0423	1
FTSE	0.0936	0.0968	0.7326
CAC	0.0834	0.0645	0.7363
Nikkei	0.1141	0.0586	0.4348

Table 2: Sample correlations of weekly return rates

The unconditional correlations of Shgh-A, Shgh-B and S&P500 indices with each other's, and with FTSE, CAC and Nikkei from weekly return rates are reported in Table 2. The correlations of developed countries with both Shgh-A and Shgh-B indices are very low which support the result of Lin et al. (2009) that investing in China Stock market reduces the portfolio risk. Since B shares are traded by foreigners, the correlation of B-share index is higher than A-shares, as anticipated, but the difference is not too much. Interestingly, although identical shares are traded in both Shgh-A and Shgh-B markets the correlation

[13] For detailed discussion see Fernald and Rogers (2002), Karolyi and Li (2003), Mei et al. (2005) and Chan et al. (2008).

between these two markets is lower than the correlation between developed countries' stock markets indices.

3.2 Empirical Results

3.2.1. STCC-GARCH Models

In accordance with our modeling procedure, firstly, the significant transition variables leading to rejection of the CCC hypothesis against STCC-GARCH specification are separately reported for A-shares and B-shares in Tables 3 and 4, respectively.

Shgh-A					
S&P500			Nikkei		
Transition variable	LM-Stat	*p*-value	Transition variable	LM-Stat	*p*-value
Time	7.340[a]	0.0067	Time	6.470[b]	0.0109
A[err.Ch]-L2	6.627[a]	0.010	err.HK-L2	3.942[b]	0.0470
A[serr.Ch]-L2	8.019[a]	0.0046	serr.HK-L2	4.411[b]	0.0357
S[serr.Ch]-L2	5.182[b]	0.0228			
serr.Ch-L1	3.455[c]	0.0630			
S[err.Ch]-L2	3.306[c]	0.0690			
err.US-L1	3.356[c]	0.0669			
FTSE			CAC		
Time	9.873[a]	0.0016	Time	9.341[a]	0.0022
A[serr.Ch]-L2	4.261[b]	0.0389	A[err.Ch]-L2	4.326[b]	0.0375
			A[serr.Ch]-L2	3.746[c]	0.0529

Notes: This table reports the LM_1 statistic of testing constant conditional correlation null hypothesis with respect to particular transition variable. The LM_1 statistics is evaluated with the estimated parameters from the restricted model of CCC model (see Silvennoinen and Teräsvirta, 2005). "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively. "-Li" is i^{th} lag of the particular variable. "Ch", "US" and "HK" represent Shgh-A, S&P500 and HSI indices. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively.

Table 3: Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable for Shgh-A Index

For Shgh-A index, the LM_1 test most strongly rejects the null hypothesis of CCC against STCC-GARCH model with time transition variable for all index pairs except S&P500. For the latter, time is the second most significant variable following a volatility measure of Shgh-A, second lag of absolute error of standardized error. However this case is not valid for Shgh-B index; time variable, except S&P500 case, cannot generate the minimum *p*-value and the null hypothesis for time variable can be rejected at 1% significance level for only S&P500. It is rejected for CAC and FTSE at 5% significance level, and cannot be rejected for Nikkei (see Table 4). To be short, the results imply that the determinants of conditional correlation between Shgh-A and

- S&P500 are time, four measures of the volatility of Shgh-A (second lag of square and absolute value of error and standardized error of Shgh-A) and the news from both Shgh-A and S&P500 indices represented by first lag of standardized error of Shgh-A and error of S&P500,

- FTSE are time and the volatility of Shgh-A (second lag of absolute value of standardized error of Shgh-A)
- CAC are time and two measures of the volatility of Shgh-A (second lag of absolute value of error and standardized error of Shgh-A),
- Nikkei are time and news from HSI index in Hong Kong (second lag of error and standardized error of HSI).

For Shgh-B index, the Table 4 reveals that the determinant of conditional correlation between Shgh-B and

- S&P500 are time, the news from both S&P500 and HSI, and volatility of Nikkei
- FTSE are time, the news from S&P500, HSI and FTSE, and volatility of Nikkei, S&P500, HSI and FTSE
- CAC are time, the news from S&P500 and volatility of Nikkei, S&P500 and CAC
- Nikkei are the news from both S&P500 and HSI, and volatility of S&P500

Shgh-B					
S&P500			Nikkei		
Transition variables	LM-Stat	*p*-value	Transition variables	LM-Stat	*p*-value
Time	9.941^{a}	0.001	err.US-L2	6.760^{a}	0.009
err.US-L2	4.396^{b}	0.036	serr.US-L2	7.174^{a}	0.007
serr.US-L2	5.536^{b}	0.018	A[serr.US]-L1	4.048^{b}	0.044
err.HK-L2	4.831^{b}	0.027	S[serr.US]-L1	4.234^{b}	0.039
serr.HK-L2	4.952^{b}	0.026	err.HK-L2	7.192^{a}	0.007
A[err.Jap]-L3	4.828^{b}	0.028	serr.HK-L2	6.489^{b}	0.011
FTSE			CAC		
Time	4.213^{b}	0.040	Time	5.429^{b}	0.019
serr.UK-L2	5.020^{b}	0.025	A[err.Fr]-L1	3.903^{b}	0.048
A[err.UK]-L2	10.727^{a}	0.001	A[err.Fr]-L2	6.004^{b}	0.014
S[err.UK]-L2	4.663^{b}	0.031	A[serr.Fr]-L1	4.368^{b}	0.036
A[serr.UK]-L2	12.927^{a}	0.000	A[serr.Fr]-L2	7.458^{a}	0.006
S[serr.UK]-L2	8.909^{a}	0.002	S[err.Fr]-L1	4.227^{b}	0.039
err.US-L2	6.910^{a}	0.008	S[serr.Fr]-L1	5.118^{b}	0.023
serr.US-L2	7.861^{a}	0.005	S[serr.Fr]-L2	5.636^{b}	0.017
A[err.US]-L2	4.550^{b}	0.033	serr.US-L2	3.924^{b}	0.047
S[err.US]-L2	5.998^{b}	0.014	A[err.US]-L2	4.376^{b}	0.036
A[serr.US]-L2	7.899^{a}	0.005	S[err.US]-L2	4.703^{b}	0.030
S[serr.US]-L2	14.668^{a}	0.000	A[serr.US]-L2	9.113^{a}	0.002
err.HK-L2	4.991^{b}	0.025	S[serr.US]-L2	14.745^{a}	0.000
serr.HK-L2	5.117^{b}	0.023	A[err.Jap]-L3	4.367^{b}	0.037
A[serr.HK]-L1	4.980^{b}	0.025	S[err.Jap]-L3	4.259^{b}	0.039
A[serr.Jap]-L1	4.360^{b}	0.036			

Notes: This table represents the LM_1 statistic to test constant conditional correlation null hypothesis with respect to particular transition variable. The LM_1 statistics is evaluated with the estimated parameters from the restricted CCC model. "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively. "-Li" is the i^{th} lag of the particular variable. "Ch", "US", "UK", "Fr", "Jap" and "HK" represent Shgh-B, S&P500, FTSE, CAC, Nikkei and HSI indices. (a) and (b) denote significance at 1% and 5% levels, respectively.

Table 4: Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable for Shgh-B Index

Since the LM_1 test delivers close *p*-values for various transition variables (Tables 3 and 4), we estimate STCC-GARCH model with all these transition variables and leave the selection of optimal one to post-estimation[14]. Table 5 presents the estimation results of conditional correlation equation for each pair which correspond to best fit[15] according to ML value. It should be noted that the indication of more than one significant transition variable by LM_1 tests puts doubts on the inferences based on STCC-GARCH model with one of them, as the DSTCC-GARCH specification may provide better description of the data under such circumstances. Consequently we mainly focus on the results of latter class of models in the next sections.

			Shgh-A			
	Transition Variable	ML Value	P_1	P_2	γ_1	c_1
S&P500	Time	-4935.216	-0.034	0.214[a]	28.3	0.639[a]
			(0.040)	(0.059)	(48.2)	(0.074)
FTSE	Time	-4940.482	-0.005	0.261[a]	400	0.651[a]
			(0.037)	(0.049)	-	(0.006)
CAC	Time	-5169.494	-0.006	0.298[a]	400	0.651[a]
			(0.04)	(0.044)	-	(0.006)
Nikkei	Time	-5234.209	0.043	0.315[a]	400	0.833[a]
			(0.035)	(0.061)	-	(0.005)
			Shgh-B			
S&P500	Time	-4773.278	-0.010	1	18.05	0.983[a]
			(0.047)	-	(16.4)	(0.033)
FTSE	A[err.UK]-L2	-4773.263	0.004	0.259[a]	400	1.343[a]
			(0.037)	(0.044)	-	(0.013)
CAC	A[serr.US]-L2	-5001.466	0.034	0.370[a]	400	1.32[a]
			(0.034)	(0.072)	-	(0.008)
Nikkei	serr.US-L2	-5054.044	0.327[a]	0.033	400	-1.27[a]
			(0.09)	(0.036)	-	(0.04)

Notes: This table reports the estimation results of parameters in conditional correlation and transition function which is described by equations (7) and (8), respectively from the STCC-GARCH model with stated transition variable. The mean and variance equations are given by (1) and (5), respectively. Values in parenthesis are standard errors. 400 is the upper constraint for speed parameters. (a) denotes significance at 1% level.

Table 5: The estimation results of STCC-GARCH model with transition variable providing best fit for both Shgh-A and Shgh-B indices

However, it is worth to note that the estimation results of best STCC-GARCH models with time variable not only verify increasing trend in the conditional correlations of Shgh-A index with S&P500, FTSE, CAC and Nikkei indices, and Shgh-B with S&P500 but also uncover the starting dates of increasing trend and the average levels of correlations reached through time[16] as discussed below.

[14] See Teräsvirta and Anderson (1992), Teräsvirta (1995), and Dijk, Terasvirta and Franses (2002)

[15] The results of STCC-GARCH model with other significant transition variables are available upon request.

[16] We search for an evidence of increasing trend in conditional correlation of Shgh-A and Shgh-B with DAX index in Germany, all shares index in Taiwan and Singapore, HSI index in Hong Kong, ASX index in Australia and Kospi index in South Korea. The results indicate that there is an increasing trend in conditional correlation between Shgh-A and all listed indices. However, increasing trend can only be identified in conditional correlation between Shgh-B and ASX and Kospi indices. The results are available upon request.

3.2.2. DSTCC-GARCH Models

Our modeling cycle continues with conducting the LM_2 test to the all estimated STCC-GARCH models for evidence of additional transition function. As before, all candidate variables in four variable groups and their lagged values are considered in testing. As far as the transition variables that delivered best STCC-GARCH models and LM_2 test results are concerned, it can be concluded that best variables in STCC-GARCH models should be one of the transition variables in double transition function specification. The LM_2 test results corresponding to significant additional transition variables for both Shgh-A and Shgh-B are presented in Table 6**.**

The null hypothesis of STCC-GARCH is rejected for those transition variables which also appear in single transition modeling. Thus, we estimate DSTCC-GARCH with all significant transition variables reported in Table 6 and leave the model selection to post estimation after eliminating unsatisfactory ones. As seen, ML values do not allow a clear cut selection among the estimated models possibly due to the fact that most of the candidate transition variables carry similar information regarding the market dynamics. We therefore elaborate the best models within each variable group to see the similarities and differences as well as to uncover the properties and structure of the conditional correlation with respect to global volatility, index specific volatility and sign of the error. Tables 7 and 8 show the estimation results of the best models within each variable group[17] for Shgh-A and for Shgh-B respectively.

<u>Shgh-A – S&P500:</u>

The empirical results in Table 7 show that among three DSTCC-GARCH models, the best fit for conditional correlation between Shgh-A and S&P500 indices is obtained with time and a volatility measure of Shgh-A, second lag of absolute value of standardized error. The conditional correlation implied by the estimated DSTCC-GARCH model is presented in Figure 3**.** The transition from low levels to high levels with respect to first transition variable, calendar time, is relatively slow and starts at the beginning of 2003 and settles down towards the middle of 2004[18]. Before 2003, the conditional correlation takes on the value of either 0.052 or -0.166 and after mid-2004 it is either 0.089 or 0.296 with respect to value of second transition variable, second lag of absolute value of standardized error of Shgh-A. The speed of transition with respect to second transition variable is very fast (γ_2 = 400). Thus there is no transition period and correlation regimes are identified according to whether the transition variable is above or below the threshold value.

[17] For example, for Shgh-A – S&P500 case, there are six significant additional transition variables. Three of them are from the third group representing index specific volatility; second lag of absolute value of error of Shgh-A and second lag of square and absolute value of standardized error of Shgh-A as a measure of Shgh-A index volatility. (Table 6). Three DSTCC-GARCH model using time and one of them as transition variable are estimated but only the estimation results of the best model corresponding to second lag of absolute value of standardized error of Shgh-A is reported in Table 7. Other three variables are among the measures of good and bad news constituting the fourth group. Two of them, first lag error and standardized error of S&P500, represents the arrival of good or bad news from S&P500 with different scaling. Therefore, among these two measures, the estimation result of DSTCC-GARCH model with transition variables of time and first lag of standardized error of S&P500 which gives better model is also reported in Table 7. Hence, instead of reporting estimation results of six models, we report three of them; one for a volatility measure of Shgh-A, one for news from S&P500 and one for news from Shgh-A.

[18] The midpoint of transition is August, 2003.

Shgh-A							
S&P500				**Nikkei**			
1st Transition Variable	Additional Transition Variable	LM-stat.	*p*-value	1st Transition Variable	Additional Transition Variable	LM-stat.	*p*-value
Time	A[err.Ch]-L2	7.291[a]	0.0069	Time	err.HK-L2	5.003[b]	0.0253
	A[serr.Ch]-L2	9.140[a]	0.0025		serr.HK-L2	5.116[b]	0.0237
	S[serr.Ch]-L2	5.078[b]	0.0242		A[err.HK]-L3	5.047[b]	0.0246
	VIX-L1	6.192[b]	0.0128		S[err.Ch]-L3	4.532[b]	0.0332
	err.US-L1	5.399[b]	0.0201		VIX-L3	4.433[b]	0.0352
	serr.US-L1	3.638[c]	0.0564				
	serr.Ch-L1	2.740[c]	0.0978				
FTSE				**CAC**			
Time	serr.Ch-L4	3.865[b]	0.0493	Time	A[err.Ch]-L2	4.490[b]	0.0341
	A[serr.Ch]-L2	5.025[b]	0.0249		A[serr.Ch]-L2	4.188[b]	0.0407
	S[serr.Jap]-L2	5.350[b]	0.0207		VIX-L3	4.264[b]	0.0389

Shgh-B							
S&P500				**Nikkei**			
1st Transition Variable	Additional Transition Variable	LM-stat.	*p*-value	1st Transition Variable	Additional Transition Variable	LM-stat.	*p*-value
Time	Time	4.302[b]	0.0381	serr.US-L2	err.US-L4	5.266[b]	0.021
	S[err.Jap]-L3	6.621[b]	0.010		vol.Jap-L1	3.911[b]	0.048
	A[err.Jap]-L3	5.597[b]	0.018		err.Jap-L4	5.284[b]	0.021
FTSE				**CAC**			
A[err.UK]-L2	serr.US-L2	3.852[b]	0.049	A[serr.US]-L2	Time	5.804[b]	0.016
	S[serr.US]-L2	5.005[b]	0.025		A[err.Fr]-L1	5.020[b]	0.024
	err.HK-L2	4.063[b]	0.043		S[err.Fr]-L1	4.320[b]	0.037
	serr.HK-L2	3.855[b]	0.049		A[serr.Fr]-L1	6.810[a]	0.009
	S[err.Jap]-L3	4.708[b]	0.030		S[serr.Fr]-L1	6.614[b]	0.010
	A[err.Jap]-L3	4.992[b]	0.025		A[err.Jap]-L3	4.632[b]	0.031
	vol.Jap-L2	5.602[b]	0.018		S[err.Jap]-L3	4.225[b]	0.029
	VIX-L3	4.233[b]	0.039				

Notes: This table represents the LM_2 statistics for testing estimated STCC-GARCH model for additional transition variable. The LM_2 statistics is evaluated with the estimated parameters from the restricted model of STCC-GARCH model (see Silvennoinen and Teräsvirta, 2009). "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively. "-Li" is the i^{th} lag of the particular variable. "Ch", "US", "UK", "Fr", "Jap" and "HK" represent Shgh-B, S&P500, FTSE, CAC, Nikkei and HSI indices. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively.

Table 6: LM statistics of testing additional transition variable for Shgh-A and Shgh-B

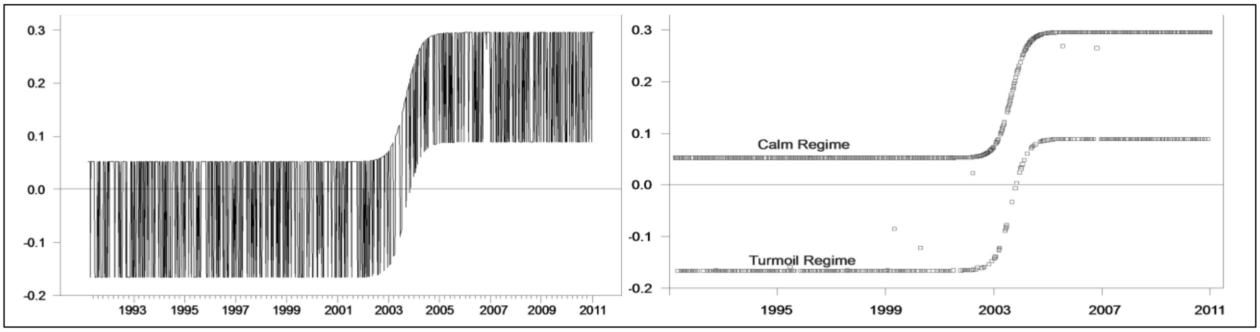

Figure 3: The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of Shgh-A

When second transition variable is less than its threshold value of 0.8, i.e. the volatility in Shgh-A is low, the conditional correlation is in the calm regime and it smoothly increases from 0.052 to 0.296 as indicated along the upper line in the graphs of Figure 3. When the volatility is relatively high (above the 0.8) the conditional correlation is in the turmoil regime and smoothly increases from -0.166 to 0.089, lower line in Figure 3. These dynamics are clearer in the second graph of Figure 3 which depicts the scatter plot of conditional correlation to the first transition variable; time. Through time, the response of conditional correlation to the second transition variable stays same and during volatile periods of Shgh-A index the correlation is at low levels[19].

DSTCC-GARCH model with time and first lag of standardized error of Shgh-A, (a measure of good and bad news) is the second best model and its conditional correlation is depicted in Figure 4. The transition with respect to time variable is slower and longer relative to first model.[20]. Before 2002, the conditional correlation is either -0.149 or 0.128, and after 2009 it fluctuates between 0.202 and 0.312 according to the value of the second transition variable. During transition period (from 2002 to 2009) the conditional correlation is a linear combination of regime specific constant correlations.

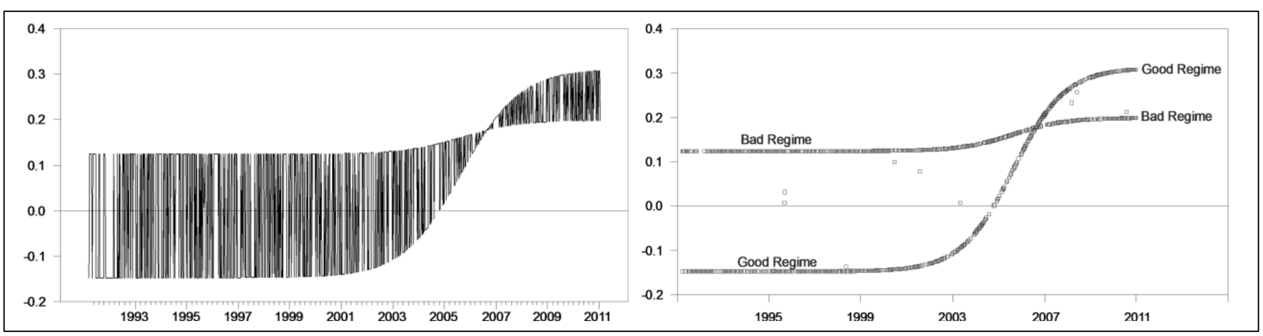

Figure 4: The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of standardized error of Shgh-A

[19] DSTCC-GARCH model for Shgh-A and S&P500 with time and VIX delivers the similar results though not reported since the model is not statistically satisfactory but available upon request.
[20] The midpoint of transition is July, 2005.

Like first model, the transition occur abruptly at very high speed (γ_2 = 400) with respect to the second transition variable. The midpoint of transition is at the estimated threshold value of 0.005, thus, the sign of the error determines the regime switches. When transition variable is less (greater) than 0.005, the correlation is in the bad (good) regime which represents the respond of conditional correlation to bad (good) domestic news. Through time the conditional correlation increased from 0.128 to 0.202 and from -0.149 to 0.312 smoothly in the former and latter regimes, respectively.

			Shgh-A							
	Transition Variables	ML Value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2
S&P500	Time + A[serr.Ch]-L2	-4929.478	0.052	-0.166[a]	0.296[a]	0.089	71.27[a]	400	0.632[a]	0.798[a]
			(0.04)	(0.042)	(0.057)	(0.059)	(13)	-	(0.039)	(0.015)
	Time + serr.Ch-L1	-4929.492	0.128[a]	-0.149[a]	0.202[a]	0.312[a]	17.33	400	0.727[a]	0.005[a]
			(0.003)	(0.031)	(0.022)	(0.1)	(16)	-	(0.071)	(0.001)
	Time + serr.US-L1	-4930.158	-0.190[a]	0.063	0.210[b]	0.275[a]	14.51	400	0.666[a]	-0.087[a]
			(0.061)	(0.062)	(0.095)	(0.065)	(9.5)	-	(0.089)	(0.030)
FTSE	Time + A[serr.Ch]-L2	-4936.814	0.040	-0.119[c]	0.337[a]	0.126[b]	400	400	0.651[a]	1.058[a]
			(0.040)	(0.066)	(0.038)	(0.060)	-	-	(0.005)	(0.024)
	Time + serr.Ch-L4	-4935.801	-0.087[c]	0.048	0.122[b]	0.372[a]	400	400	0.652[a]	-0.428[a]
			(0.051)	(0.043)	(0.05)	(0.05)	-	-	(0.005)	(0.013)
CAC	Time + A[serr.Ch]-L2	-5165.291	0.05	-0.116[a]	0.372[a]	0.162[a]	400	400	0.651[a]	0.906[a]
			(0.034)	(0.02)	(0.007)	(0.056)	-	-	(0.006)	(0.04)
Nikkei	Time + serr.HK-L2	-5228.582	0.082[b]	-0.184[b]	0.352[a]	-0.018	400	400	0.804[a]	0.844[a]
			(0.04)	(0.087)	(0.066)	(0.165)	-	-	(0.01)	(0.024)
	Time + VIX-L3	-5228.866	0.059	0.002	0.621[a]	0.198[b]	400	400	0.834[a]	21.57[a]
			(0.042)	(0.06)	(0.076)	(0.089)	-	-	(0.003)	(0.022)
	Time + A[err.HK]-L3	-5231.045	0.053	-0.067	0.397[a]	0.024	400	400	0.834[a]	5.933[a]
			(0.036)	(0.14)	(0.064)	(0.162)	-	-	(0.005)	(0.131)

Notes: This table reports the estimation results of parameters in conditional correlation and transition function (equations (11) and (8), respectively) from DSTCC-GARCH model with the stated transition variables. The mean and variance equations are given by (1) and (5), respectively. Values in parenthesis are standard errors. 400 is the upper constraint for speed parameters. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively. "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively."-Li" is the i^{th} lag of the particular variable. "Ch", "US", "UK", "Fr", "Jap" and "HK" represent Shgh-B, S&P500, FTSE, CAC, Nikkei and HSI indices.

Table 7: The estimation results of DSTCC-GARCH models for Shgh-A.

An important fact revealed by the second transition variable in Figure 4 is that during whole period low or high correlation levels are not specific to good or bad news due to structural change in the response of conditional correlation to news from Shgh-A in 2006. Up to this year, the conditional correlation shifts up to higher correlation (from -0.149 to 0.128) when bad domestic news appears. After this year, instead of increasing, the conditional correlation shifts down to lower levels (from 0.312 to 0.202) coinciding with bad domestic news. This change may be attributed possibly to foreign investor starting to trade in A-shares and/or the other structural reforms that took place in Chinese financial markets.

Our finding of structural change with respect to the first lag of standardized error of Shgh-A may provide an answer to the failure of literature in finding evidence of upward trend in conditional correlation among Shgh-A and S&P500. Since the widely used DCC-GARCH model employs standardized errors in the correlation equations and do not take structural change[21] in to account, they failed to detect an evidence of increasing trend. In our model, we implicitly assume that there can be change in the dynamics of correlation with respect to standardized error or any other transition variable without imposing any restriction on the regime specific correlation parameters and hence the model is able to capture the increasing trend with structural breaks. This structural change with respect to standardized error of Shgh-A can also help to explain why this variable rejects CCC hypothesis with low LM_1 statistics. The LM statistics employ linear approximation, so the effects of this variable on conditional correlation diminish.

Finally, the effects of news from S&P500 on the estimated conditional correlation are plotted in the Figure 5. Similar to second model, bad regime is defined when the first lag of standardized error of S&P500 is less than threshold value of -0.087 or when bad news arrive from S&P500. The transition to the higher correlation levels starts in 2001 and ends in 2008[22]. During this transition period, the conditional correlations increase smoothly from -0.19 to 0.21 and from 0.063 to 0.275 in the bad and good regimes respectively. At first glance, the results seem to be similar with the results of the second DSTCC-GARCH model with time and first lag of standardized error of Shgh-A but with very important difference: low correlation levels correspond to bad regimes for both before and after the transition to higher correlation levels for whole period. With the structural change in 2006, this difference vanishes and the conditional correlation starts to give same response to news from both Shgh-A and S&P500; the correlation level declines when a bad news appears.

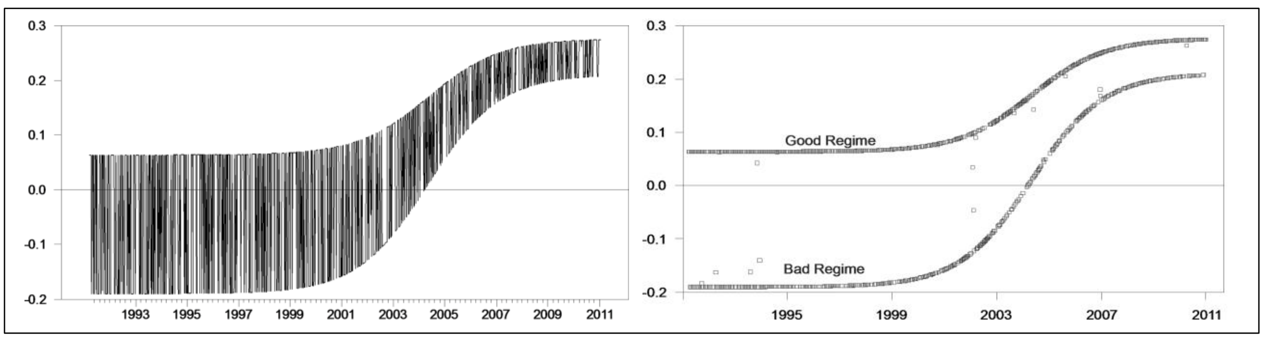

Figure 5: The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of standardized error of S&P500

The low levels of conditional correlation following bad news from S&P500 implies that Shgh-A has offered valuable opportunities to reduce risk in terms of international portfolio diversification to the US investors in times of decline in the US stock markets since July 2003 when authorized foreign investors are allowed to trade in A-shares.

[21] Cappiello et al. (2006) aim to detect structural change with dummy variables and they apply asymmetric model which can identify the differences between positive and negative standardized error. However their estimation results are not satisfactory when they use dummy for both intercept and slope parameters, so they use dummy for only intercept term which can detect shift in mean of conditional correlation. Even if they used slope dummy variable they could not identify the structural change in the case of non-zero threshold value.

[22] The midpoint of transition is April, 2004.

Figures 4 and 5 reveal another important result that before 2002 the conditional correlation between Shgh-A and S&P500 fluctuates in a wider range relative to post 2002 period with respect to the sign of the new information from both China and the US. Thus, following the foreign investors' entry in mid-2003 and structural reforms that took place between 2001 and 2006, the magnitudes of reaction to the arrival of news have reduced to nearly one third and became insignificant after 2009 indicating diminishing role of news from Shgh-A and S&P500 in explaining correlation dynamics since then.

It is illuminating to note that implied zero correlation before 2002 and 0.214 after this date by STCC-GARCH model (Table 5) may be considered as the average values of correlations delivered by the best DSTCC-GARCH model for their respective states (-0.166 and 0.052 ; 0.089 and 0.296), if the model is not controlled for the second transition variable.

Shgh-A – FTSE:

Similar to Shgh-A – S&P500 case, as a second transition variable, second lag of absolute value of standardized error of Shgh-A, rejects the null hypothesis of STCC-GARCH model with time transition variable, see Table 6. The conditional correlation between Shgh-A and FTSE implied by the first DSTCC-GARCH model with time and this second transition variable is depicted in the upper graphs of Figure 6. The speeds of transition are very high for both transition variables, thus conditional correlation is equal to one of the four regimes specific conditional correlations throughout the whole period. The switch to the higher correlation levels takes place in December 2003. The conditional correlation takes value of either 0.04 or -0.119 before this date and since then, and it fluctuates between 0.126 and 0.337. Through time the conditional correlation shifts down to lower levels during volatile periods of Shgh-A. Although this second transition variable generates almost same conditional correlation dynamics for Shgh-A – S&P500 and Shgh-A – FTSE pairs, the threshold value (0.8) which identifies the calm and turmoil regimes is lower for former pair compared to the value of latter pair which is 1.058 suggesting that S&P500 is more sensitive to volatility increases in Shgh-A compared to FTSE.

The second DSTCC-GARCH model which uses time and the fourth lag of standardized error of Shgh-A implies very comparable conditional correlation patterns to the first model. Estimated threshold value for the second transition variable is different than zero and therefore does not allow identification of specific regimes as good and bad. As seen, in lower graphs of Figure 6, when the fourth lag of standardized error is less than threshold value, -0.428, the correlation jumps from -0.087 to 0.122 and when it is above, the correlation rises from 0.048 to 0.372 in the beginning of 2004. Before this year, the conditional correlation fluctuates between -0.087 and 0.048, and since then it fluctuates between 0.122 and 0.372. Both in pre-2004 and post-2004 periods the conditional correlation shifts to lower regime when things start to worsen in Shgh-A. Unlike Shgh-A – S&P500 pair, the effects of news from Shgh-A does not die out but preserves its importance.

The STCC-GARCH model with time transition variable indicates no significant correlation between Shgh-A and FTSE until the beginning of 2004. However, before this date, the DSTCC-GARCH estimates indicate that the conditional correlation moves on average between -0.1 and 0.044. Once again, the zero correlation before 2004 and the correlation level of 0.261 after this date implied by STCC-GARCH model

(Table 5) may be thought as the average value of regime specific correlation of DSTCC-GARCH model through time.

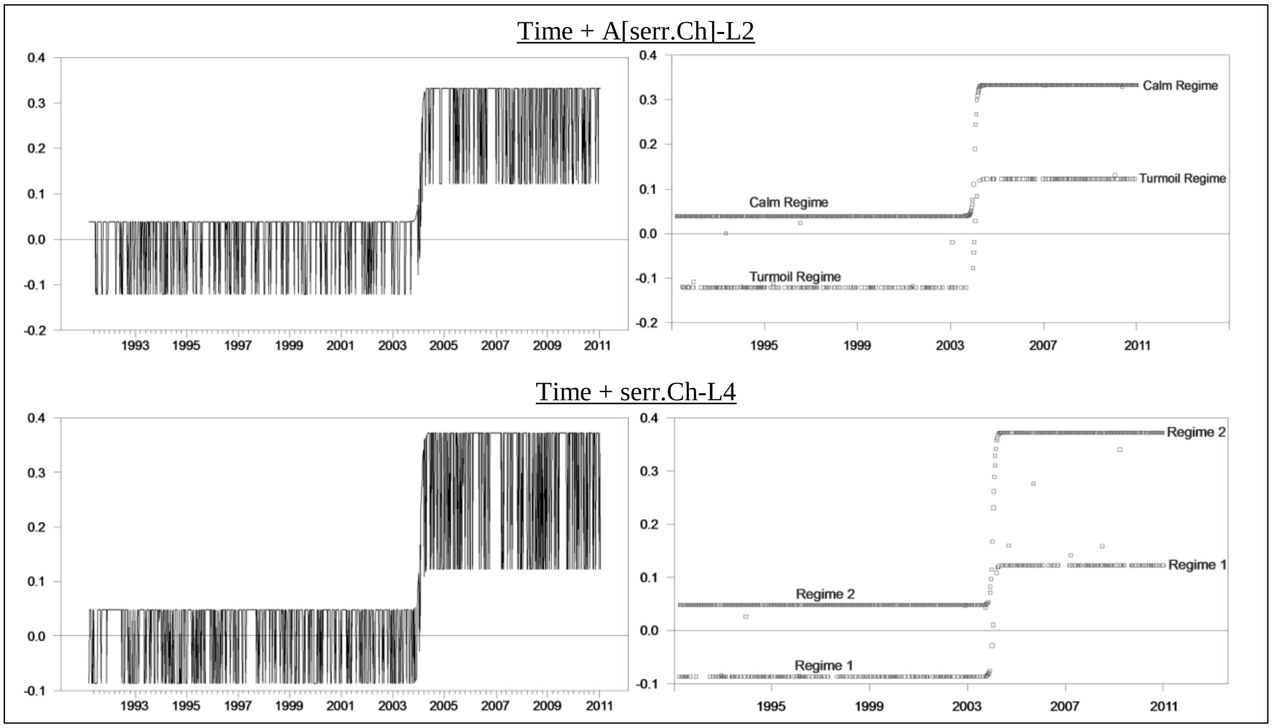

Figure 6: The conditional correlation between Shgh-A and FTSE from the DSTCC-GARCH models

Shgh-A – CAC:

As in Shgh-A-S&P500 and Shgh-A-FTSE pairs, the second lag of absolute value of standardized error of Shgh-A is one of the significant second transition variables (Table 6) and Table 7 shows, like S&P500 case, this transition variable with time generates the best DSTCC-GARCH model for Shgh-A – CAC. The dynamics of estimated conditional correlation is very similar to one with FTSE and S&P500 as depicted in Figure 7.

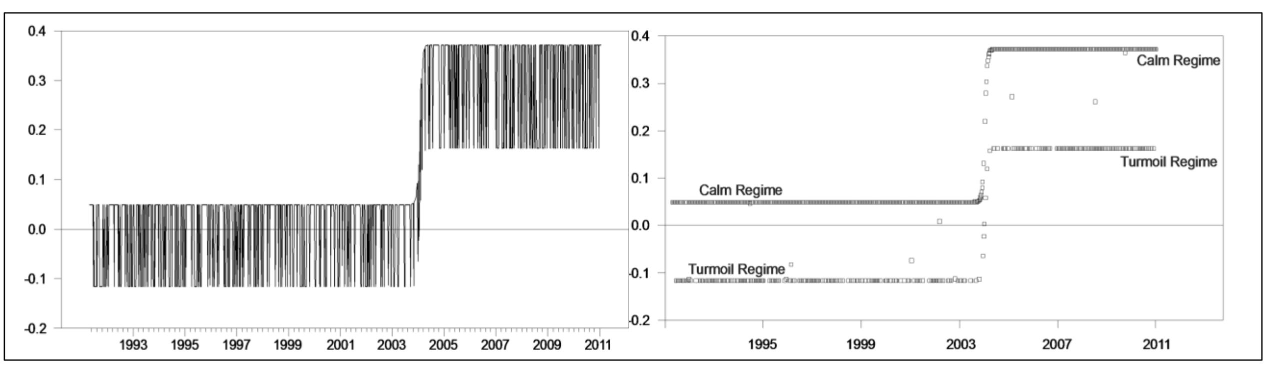

Figure 7: The conditional correlation between Shgh-A and CAC from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of Shgh-A

The transition to the higher correlation levels occurs abruptly at the end of 2003. The conditional correlation fluctuates between -0.116 and 0.05, and 0.162 and 0.372 before and after 2004 respectively. Similar to S&P500 and FTSE cases, the conditional correlation shifts down to lower levels during volatile periods of Shgh-A. The only difference is the threshold value which determines the calm and turmoil regimes. The CAC is more (less) sensitive to rise in volatility of Shgh-A than FTSE (S&P500).

No correlation before 2004 and 0.298 after 2004 captured by STCC-GARCH model (Table 5) with time correspond to the average of the DSTCC-GARCH estimates, (-0.116 or 0.05) before 2004 and (0.162 or 0.372) after 2004.

Shgh-A – Nikkei:

The conditional correlation between Shgh-A and Nikkei implied by successful DSTCC-GARCH models are depicted in Figure 8.

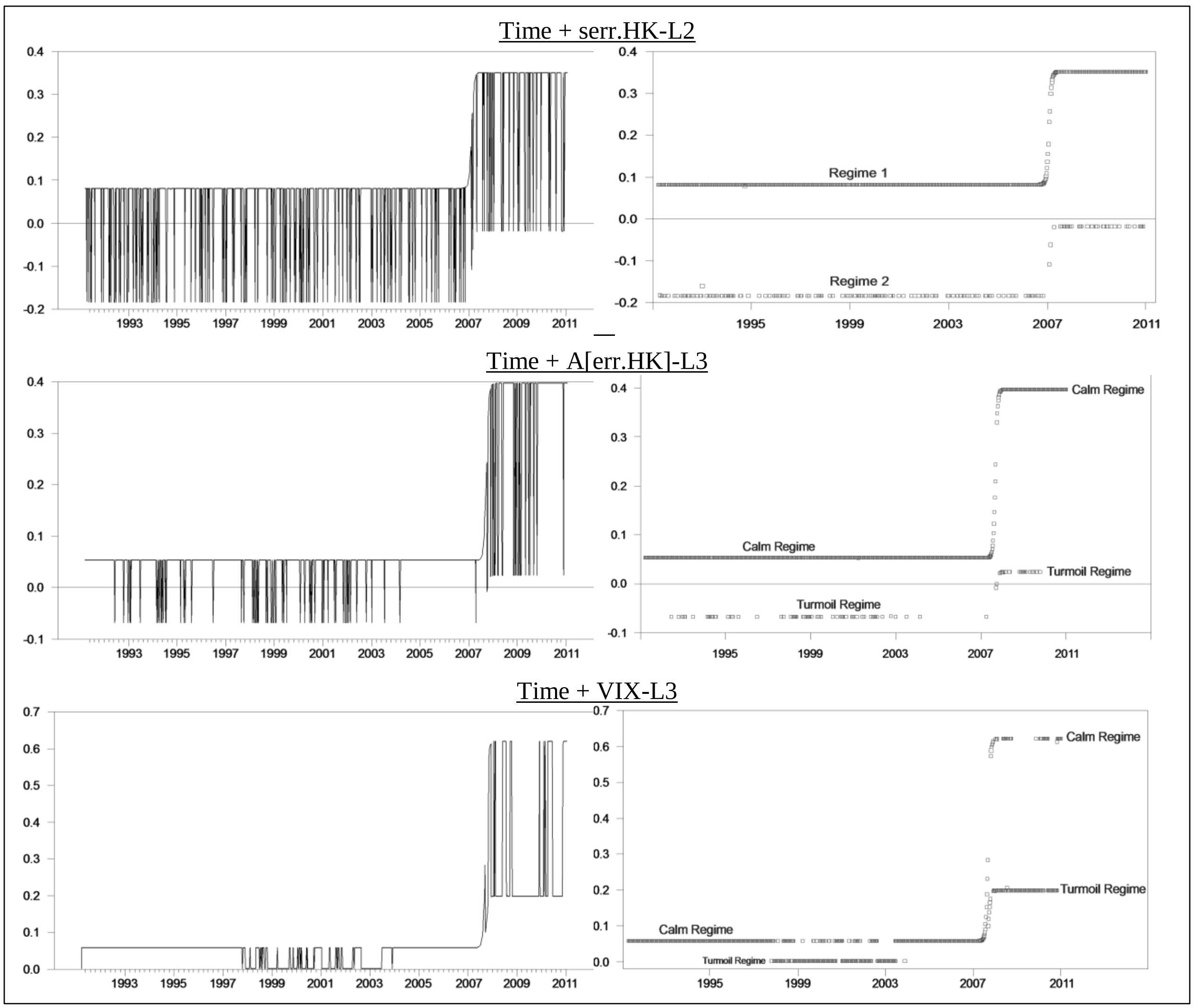

Figure 8: The conditional correlation between Shgh-A and Nikkei from the DSTCC-GARCH models

The upper graphs correspond to the first DSTCC-GARCH model using time and a measure of good and bad news from HSI; second lag of standardized error of HSI. The transitions with respect to both transition variables occur very sharply. Hence the conditional correlation equals to one of the four regimes specific correlations through time and shifts up to higher levels in January 2007. Before 2007, the conditional correlation fluctuates between 0.082 and -0.184 and since then it moves between 0.352 and -0.018 depending on whether second transition variable is above or below its threshold. The correlation levels of zero and 0.315 implied by STCC-GARCH model (Table 5) can be interpreted as the average of these correlation levels. The non-zero threshold value (c_2 = 0.844) does not permit identification of specific regimes as good and bad. In January 2007, the conditional correlation shifts up from 0.082 to 0.352 and from -0.184 to -0.018 when this transition variable is below and above its threshold value of 0.844 respectively.

Similar to Shgh-A – S&P500 case, global volatility is indicated as significant transition variable after controlling for time trend. When the results of DSTCC-GARCH with time and third lag of VIX index and time and absolute value of error of HSI are examined, up to September 2007 there is no significant correlation between Shgh-A and Nikkei. But, since then, the correlation starts to give respond to these volatility measures and it is either 0.198 or 0.621 and either 0.024 or 0.397 according to former and latter additional transition variables, respectively. The model with VIX recognizes the values of index which are greater than 21.57 as turmoil regime. For the third specification, this regime is identified when the third lag of absolute value of error of HSI is greater than 5.933. In both models, low correlation levels are associated with turmoil regimes.

Thus, increasing trend in the conditional correlations of Shgh-A index with S&P500, FTSE, CAC and Nikkei indices are identified. Not surprisingly, the starting date of increasing trend between Shgh-A index and other indices ranges from 2002 to 2007 supporting the idea that financial reforms that took place in China between 2001-2006 have paved the way of integration of markets in China with the rest of the world particularly after 2002 and hence partially eliminating portfolio diversification benefits since then.

Although the sample used in the paper of Lin et al (2009) covers the years when increasing trend in correlation is started, they cannot identify the increasing trend in the correlation possibly due to their usage of DCC-GARCH model. In DCC-GARCH modeling, the first lags of standardized errors are used as default explanatory variable in the conditional correlation equation. However, as our results show these variables are rarely selected as optimal transition variable and time trend has more dominant explanatory power than standardized errors for the conditional correlation between Shgh-A and all other indices. Thus it may be concluded that default explanatory variables in DCC-GARCH models are not appropriate for examining conditional correlation of stock markets in China explaining the poor results of the earlier literature.

<u>Shgh-B – S&P500:</u>

As presented in Table 6, two volatility measures of Nikkei, third lag of absolute value of error and third lag of square of error, are indicated as second transition variables in addition to time. The DSTCC-GARCH model using time and the former variable delivers the best fit for the conditional correlation between Shgh-B and S&P500 indices (Table 8). Figure 9 clearly show that the conditional correlation starts to increase in 2001 with very low speed. Thus the transition to the higher levels has not settled down yet and the regime specific correlations, 0.111 and 0.841, corresponding to the higher correlation levels are not attained. Therefore, since 2000 the conditional correlation equals to linear combination of regime specific constant correlations. Before 2000, the conditional correlation is very close to zero and fluctuates between -0.029 and -0.057 depending on whether the second transition variable is greater or less than its threshold value, 1.77. During the transition period, the increasing trend in conditional correlation between Shgh-B and S&P500 is interrupted by rise in the volatility of Nikkei and correlation shifts down to lower levels if the second transition variable is above its threshold, i.e. the volatility of Nikkei is high.

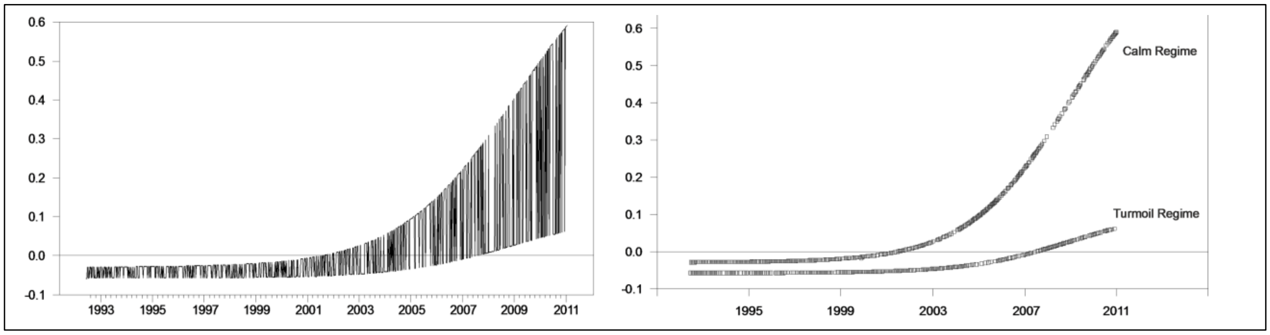

Figure 9: The conditional correlation between Shgh-B and S&P500 from the DSTCC-GARCH model with time and third lag of absolute value of error of Nikkei

Other successful DSTCC-GARCH model for Shgh-B - S&P500 pair is the one which uses time in both transition functions. Although ML does not select this model, the dynamics of estimated conditional correlation from DSTCC-GARCH model with time and time seem to be interesting and it is depicted in Figure 10. It seems that there are two important shifts in correlation through time. In the first one, correlation shifts from -0.08 to 0.074 in August 1999. The second shift takes place in March 2009 and levels at 0.465 which can be thought as the average of correlations levels implied by third lag of absolute value of error of Nikkei after this date.

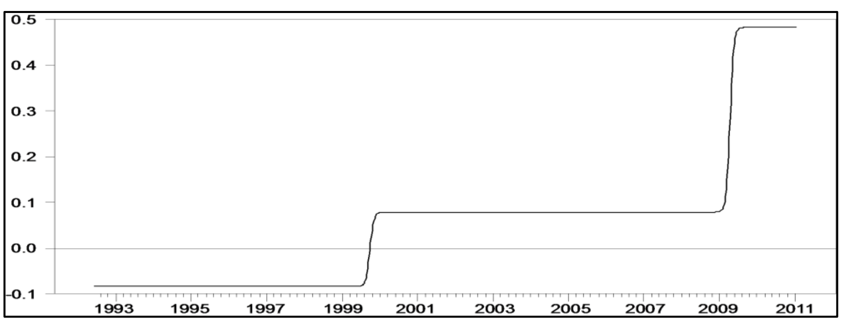

Figure 10: The conditional correlation between Shgh-B and S&P500 from the DSTCC-GARCH model with time and time

	Shgh-B									
	Transition Variables	ML Value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2
S&P500	Time + A[err.Jap]-L3	-4768.385	-0.029	-0.057	0.841	0.111	8.97	400	0.899[b]	1.77[a]
			(0.070)	(0.08)	(1.287)	(0.425)	(13.3)	-	(0.359)	(0.03)
	Time + Time	-4769.997	-0.08	0.074[c]	-	0.465[a]	400	400	0.436[a]	0.912[a]
			(0.055)	(0.044)	-	(0.092)	-	-	(0.008)	(0.005)
FTSE	A[err.UK]-L2+serr.HK-L2	-4766.773	0.062	-0.309[a]	0.298[a]	0.116	400	400	1.27[a]	0.59[a]
			(0.044)	(0.109)	(0.046)	(0.105)	-	-	(0.024)	(0.009)
	A[err.UK]-L2+serr.US-L2	-4770.693	0.066	-0.198[c]	0.273[a]	0.294[a]	400	400	1.68[a]	0.744[a]
			(0.043)	(0.107)	(0.056)	(0.10)	-	-	(0.038)	(0.017)
	A[err.UK]-L2+S[serr.US]-L2	-4770.582	0.061	-0.111[a]	0.171[a]	0.312[a]	400	400	1.266[a]	0.549[a]
			(0.059)	(0.007)	(0.048)	(0.022)	-	-	(0.016)	(0.01)
	A[err.UK]-L2+VIX-L3	-4770.646	0.066	-0.139[b]	0.284[a]	0.217[a]	400	400	1.27[a]	21.57[a]
			(0.046)	(0.061)	(0.057)	(0.063)	-	-	(0.012)	(0.035)
	A[err.UK]-L2+A[err.Jap]-L3	-4770.111	0.117[c]	-0.06	0.371[a]	0.208[a]	400	400	1.345[a]	0.698[a]
			(0.072)	(0.055)	(0.086)	(0.057)	-	-	(0.023)	(0.05)
CAC	A[serr.US]-L2 + Time	-4994.882	-0.044	0.315[a]	0.213[a]	0.522[a]	400	400	1.32[a]	0.735[a]
			(0.043)	(0.1)	(0.062)	(0.089)	-	-	(0.01)	(0.007)
	A[serr.US]-L2+A[serr.Fr]-L1	-4996.685	-0.004	0.123[b]	0.29[a]	0.655[a]	400	400	1.32[a]	1.05[a]
			(0.005)	(0.059)	(0.076)	(0.061)	-	-	(0.005)	(0.02)
	A[serr.US]-L2+A[err.Jap]-L3	-4996.528	0.062[c]	-0.27[b]	0.373[a]	-0.622[a]	400	400	1.32[a]	4.71[a]
			(0.036)	(0.118)	(0.074)	(0.168)	-	-	(0.008)	(0.028)
Nikkei	serr.US-L2 + err.Jap-L4	-5045.393	0.102	0.317[a]	-0.375[a]	0.069[c]	400	400	-1[a]	-3.66[a]
			(0.252)	(0.077)	(0.082)	(0.039)	-	-	(0.015)	(0.195)

Notes: This table reports the estimation results of parameters in conditional correlation and transition function (equations (11) and (8) respectively) from DSTCC-GARCH model with the stated transition variables. The mean and variance equations are given by (1) and (5), respectively. Values in parenthesis are standard errors. 400 is the upper constraint for speed parameters. (a), (b), and (c) denote significance at 1%, 5%, and 10% levels, respectively. "err" and "serr" are error and standardized error from GARCH (1,1) process. A[.] and S[.] represent absolute value and square of brackets respectively."-Li" is the i-th lag of the particular variable."Ch", "US", "UK", "Fr", "Jap" and "HK" represent Shgh-B, S&P500, FTSE, CAC, Nikkei and HSI indices.

Table 8: The estimation results of DSTCC-GARCH models for Shgh-B

Shgh-B – FTSE:

The best STCC-GARCH model for the conditional correlation between Shgh-B and FTSE is not obtained with time but with the second lag of absolute value of error of FTSE which is a measure of FTSE volatility. The STCC-GARCH estimates in Table 5 indicate that the conditional correlation shifts from zero to 0.259 when the volatility of FTSE increases above its threshold value of 1.343. LM_2 test results in Table 6 show that the null hypothesis of STCC-GARCH model is rejected for eight additional transition variables not including time suggesting that increasing trend hypothesis is not valid for Shgh-B – FTSE pair.

DSTCC-GARCH models with all significant additional variables are estimated and the estimation results of five successful DSTCC-GARCH models are reported in Table 8. Among these models, the DSTCC-GARCH model with the second lag of absolute value of error of FTSE and second lag of standardized error of HSI provides the highest ML value. The conditional correlation as a function of these variables is plotted in Figure 11. The speeds of transitions with respect to both transition variables are very high, so there is no transition period and conditional correlation takes on one of the values of the four regime specific correlations through time. If the second lag of absolute value of error of FTSE is less than its threshold value, 1.27 (or when the volatility of FTSE is low), the conditional correlation is 0.062 when the value of second lag of the standardized error of HSI is less than its threshold value 0.59 and it is -0.309 otherwise. Similarly, during turmoil periods of FTSE the conditional correlation is either 0.298 or 0.116 according to the value of second transition variable. Thus the conditional correlation between Shgh-B and FTSE increases with the rise in the volatility of FTSE and with the decline in standardized error in HSI. Therefore the highest correlation level, 0.298, is attained when the second lag of absolute value of error of FTSE is greater than its threshold and the second lag of the standardized error of HSI is less than its threshold.

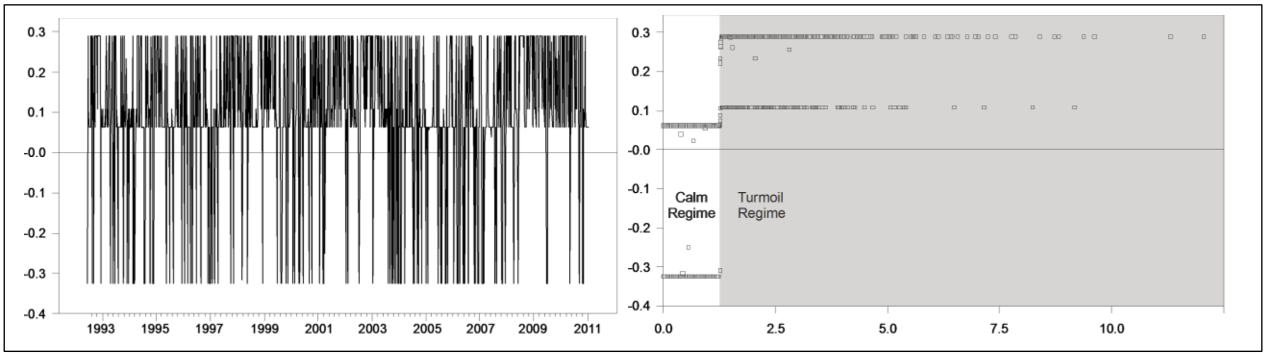

Figure 11: The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of HSI

Like news from HSI, the news from S&P500 carries significant information in explaining conditional correlation between Shgh-B and FTSE. The DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of S&P500 which is plotted in Figure 12, imply that during low volatility of FTSE the conditional correlation is either 0.066 if the second transition variable is less than its threshold value of 0.744 or -0.198 if it is higher.

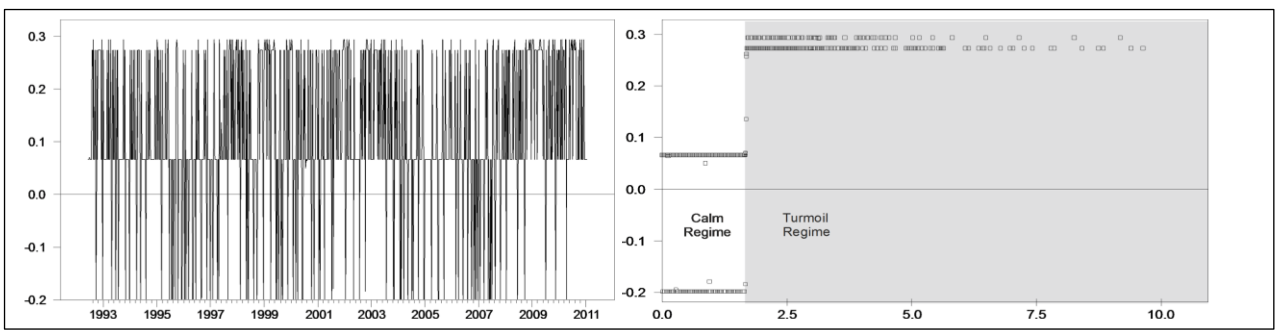

Figure 12: The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of S&P500

However, during high volatile periods of FTSE, the news from S&P500 index losses its importance and conditional correlation is about 0.28. Therefore, there are three effective regimes in this case. Like the first DSTCC-GARCH model, if the volatility of FTSE rises above its threshold and standardized error of S&P500 declines below its threshold the conditional correlation shift up to higher levels.

On the other hand, using volatility measures, second lag of square of standardized error of S&P500 and third lag of VIX, as a second transition variable in the third and fourth DSTCC-GARCH models whose first transition variables are second lag of absolute value of error of FTSE generates four effective regimes (see second graphs in Figure 13). Since the estimated threshold values of first transition are very close (see Table 8; 1.266 vs. 1.27), these models' calm and turmoil regimes with respect to volatility measure of FTSE seem to be coinciding. During low volatile periods of FTSE (when the first transition variable, second lag of absolute value of error of FTSE, is less than its threshold value) the conditional correlation is either 0.061 or -0.111 and 0.066 or -0.139 according to the volatility of S&P500 and global volatility, respectively. Similarly, it fluctuates between 0.171 and 0.312, and 0.217 and 0.284 if the volatility in FTSE is high. At first glance, it seems that these volatility measures, volatility of S&P500 and global volatility, imply almost same regime specific correlation levels. However, as it can be seen from Figure 13, they generate very different dynamics.

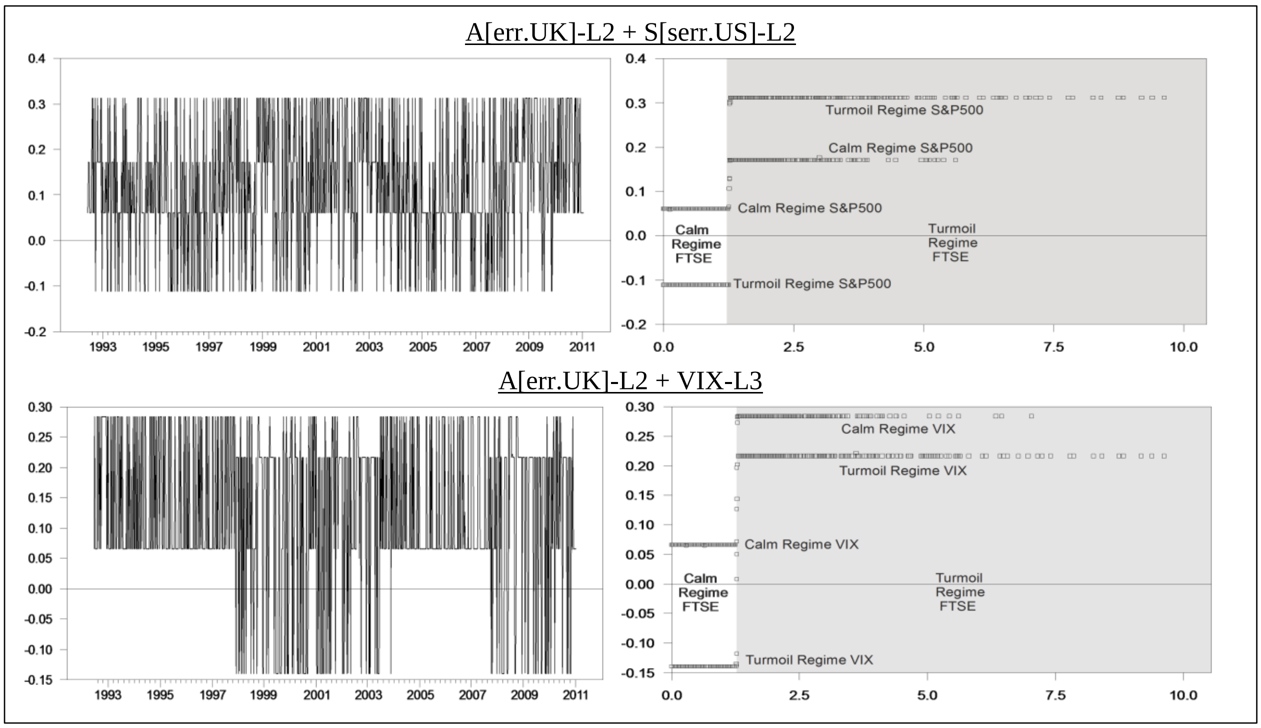

Figure 13: The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH models

During tranquil periods in both FTSE and S&P500 the correlation is very close to zero but when the volatility of S&P500 rises above its threshold value, 0.549, the correlation declines to -0.111. On the other hand, a rise in the volatility of S&P500 beyond its threshold leads to an increase in conditional correlation from 0.171 to 0.312 during high volatile times in FTSE. Thus the highest correlation level is attained during turmoil periods in both FTSE and S&P500. Unlike volatility of S&P500, global volatility leads to a decrease in conditional correlation independent of the state of the FTSE.

Shgh-B – CAC:

A volatility measure of S&P500, second lag of absolute value of standardized error, delivers the best STCC-GARCH specification for Shgh-B – CAC pair (Table 5) and the estimation results show that the conditional correlation is very close to zero if the volatility in S&P500 is low. But when the volatility rises above its threshold, 1.32, the correlation shifts up to 0.37. For this pair, time variable, which is one of the significant transition variables in STCC modeling, appears among the significant second transition variables in addition to the best first transition variable and produces the best DSTCC-GARCH model. Thus, increasing trend in conditional correlation is also valid for Shgh-B – CAC case. The conditional correlation between Shgh-B and CAC implied by these transition variables are presented in Figure 14.

The transition to higher correlation levels takes place in August 2005. Up to this date, the conditional correlation is around zero if the volatility of S&P500 is low or in other words if the second lag of absolute value of standardized error of S&P500 is below its threshold, 1.32, but it increases to 0.315 during turmoil periods. After 2006 it is 0.213 during calm times and shifts up to 0.522 when the volatility increases. Both before and after the transition the conditional correlations move to higher levels when the volatility of S&P500 rises.

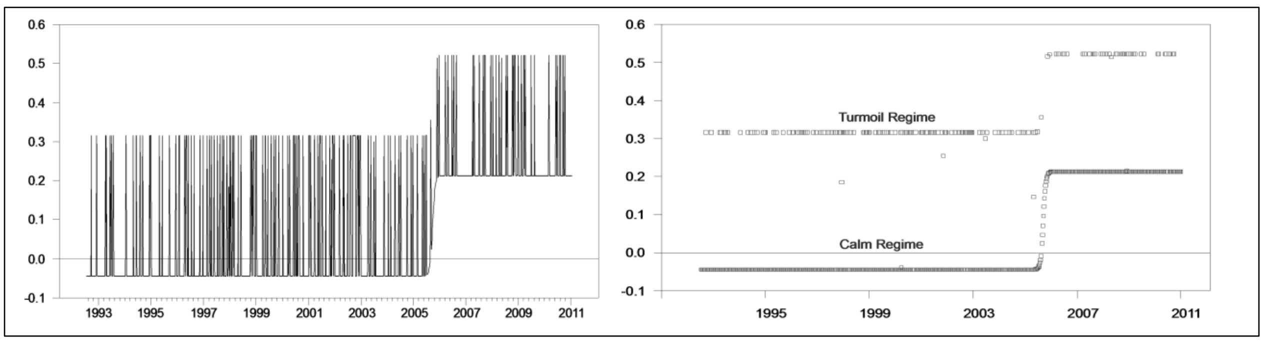

Figure 14: The conditional correlation between Shgh-B and CAC from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of S&P500

Shgh-B – Nikkei:

The best STCC-GARCH model using the second lag of standardized error of S&P500 (Table 5) defines two regime specific correlations, 0.327 and 0.033. The conditional correlation is 0.327 if this transition variable is less than its threshold, -1.27. But it is very close to zero if the standardized error is greater than this value. The null hypothesis of STCC-GARCH model is rejected by three additional transition variables (Table 6). The only successful DSTCC-GARCH model which is reported in Table 8 employs second lag of standardized error of S&P500 and fourth lag error of Nikkei. The threshold values of both transition variables are non-zero obscuring regime identifications as good and bad, and the conditional correlation between Nikkei and Shgh-B is governed by three effective regimes. As Figure 15 clearly indicates, the conditional correlation is -0.375 if the fourth lag of error of Nikkei is less than its threshold[23], -3.66, and it is either 0.069 or 0.317 if it is greater.

[23] In fact, it is either 0.102 or -0.375 when the fourth lag of error of Nikkei is less than its threshold. But there are only ten values equal to 0.102, making regime identification implausible.

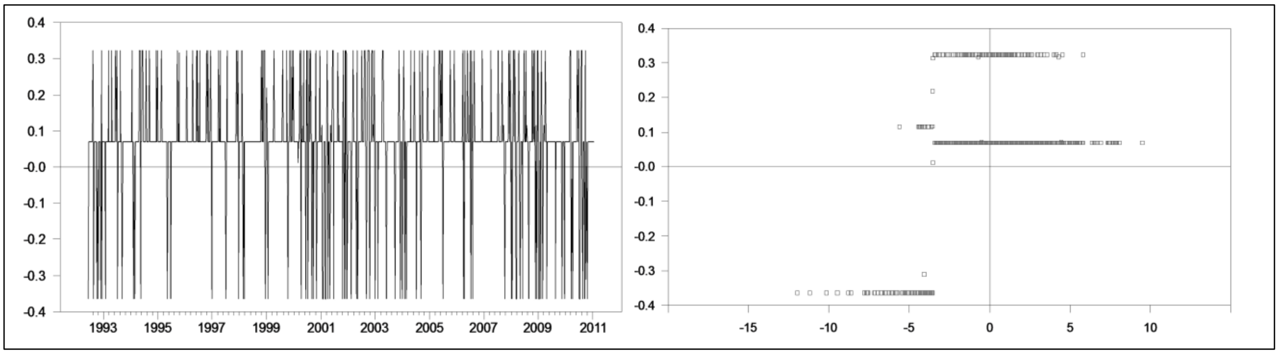

Figure 15: The conditional correlation between Shgh-B and Nikkei from the DSTCC-GARCH model with second lag of standardized error of S&P500 and fourth lag error of Nikkei

Similar to STCC specification, this best DSTCC-GARCH model indicates that when the first transition variable, second lag of standardized error of S&P500, is below its threshold the conditional correlation equals to 0.317. However, unlike STCC, when the first transition variable is greater than its threshold, conditional correlation takes on two values (-0.375 and 0.069) whose average value (0.033) is given by STCC specification.

4. Conclusion

This paper investigates the dynamic structure of return correlation between stock markets in China, Shgh-A and Shgh-B, and stock markets in the US, UK, France and Japan. We employ smooth transition conditional correlation (STCC-GARCH) and double smooth transition conditional correlation (DSTCC-GARCH) models to seek for an evidence of increasing trend in the conditional correlation of both Shgh-A and Shgh-B indices with S&P500, FTSE, CAC and Nikkei indices and to reveal the structure and the properties of correlation with respect to global volatility, index specific volatility and the sign of the news from the indices whose effects on the dynamic nature of conditional correlation is of interest for a long time in the literature.

The empirical results reveal evidence of increasing trends in the conditional correlations of Shgh-A index with S&P500, FTSE, CAC and Nikkei indices and Shgh-B with S&P500 and CAC with the exception of Shgh-B – FTSE and Shgh-B – Nikkei pairs. It seems that the starting years of transition from low to high correlation range from 2002 to 2007 for various pairs which correspond to financial reforms period in China. Before the transition to the higher levels, the conditional correlations are very close to zero for all index pairs but moves to high levels since 2007 though not as high as the ones observed among the indices of developed countries. Therefore Chinese stock markets can still provide valuable opportunities for portfolio diversification. Moreover, the results of DSTCC-GARCH specifications show that market volatility plays significant role and uncover that volatile periods lead to lower correlation compared to calm periods for Shgh-A. On the other hand, for Shgh-B, the effects of market volatility are mixed. While increases in volatility of FTSE, CAC and S&P500 lead to increase in the conditional correlation of Shgh-B, the volatility of Nikkei and global volatility lead to decrease.

5. References

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