Extreme Risk Spillover Between Chinese Stock Markets and International Stock Markets

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ABSTRACT

In this paper, we provide an empirical study on spillover of extreme downside market risk among Shares A, B and H in the Chinese stock market, between different stock markets in Greater China, and between the Chinese stock market and other international capital markets. It is found that there exists strong risk spillover between Share A indices and Share B indices, and the occurrence of a large downside risk in Share B markets can help predict the occurrence of a similar future risk in Share A markets. There also exists strong risk spillover between Share A and Share H, and particularly between Share B and Share H. Share B, and particularly Share H, have significant risk spillover with the Asian and international stock markets. In contrast, although Share A has some risk spillover with Korean and Singapore stock markets, it has no risk spillover with leading international mature capital markets—Japan, U.S. and Germany. Our findings suggest that the market segmentation between Share A and Share B is effective in avoiding large adverse shocks from international capital markets. In terms of large adverse market movements, the Chinese stock market has some ties with the Asian stock markets, but its link with leading international capital markets is still weak.

Key Words: Chinese stock market, Extreme downside risk, Financial contagion, Granger causality in risk, Risk spillover, Value at Risk

1. INTRODUCTION

One key to the rapid growth of Chinese economy over the last twenty five years is the opening door policy to the outside world. With increasing integration into world economy, Chinese economy has enjoyed tremendous efficiency gain. At the meantime, the increasing international link also renders Chinese economy more prone than ever to international shocks. In this paper, we will investigate the influence of international capital markets on Chinese stock market. In particular, we will examine whether and how extreme downside market risk is transmitted between Chinese stock market and overseas capital markets. Such a study is important for investment/portfolio diversification, risk management, and sustained steady growth of Chinese economy.

The setup of Chinese stock market is one of the most innovative ideas for Chinese economic reform that was initiated in 1978. Although started only about a dozen of years ago, Chinese stock market has developed rapidly and has become the largest emerging capital market in the world (e.g., Chen and Hong 2003). In order to attract international capital inflows while avoiding or alleviating adverse international shocks on Chinese stock market, China designed two segmented stock markets in the early 1990s. As is well-known, China has two stock exchanges—Shanghai stock exchanges (SHSE) and Shenzhen stock exchanges (SZSE). A firm listed on SHSE or SZSE can issue two types of a common stock: Share A and Share B.[1] Share A is designed for domestic investors trading in local currency, and Share B is designed for foreign investors trading in foreign currencies.[2] Moreover, some Chinese companies are allowed to go beyond traditional domestic equity-financing channels to raise capital by listing in oversea capital markets such as Hong Kong and New York stock exchanges. These are the so-called Share H and Share N.[3] For a detailed account of the market structure of Share H, see (e.g., Xu 2000). Obviously, different Shares of a common stock have different degrees of link with international capital markets. Most international shocks are expected to be mainly absorbed in Share B markets and their impact on Share A markets will become diminished. However, with increasing integration between Share A and Share B markets, and between Chinese stock market and international capital markets, mutual interaction between Chinese stock market and overseas capital markets is expected to become stronger as time evolves. The possibility of financial contagion, such as one similar to the 1997-1998 Asian financial crisis, becomes larger.

Given the important role Chinese stock market plays and its increased link with international capital markets, controlling and monitoring financial risk in Chinese stock market has been receiving more and more attention from business practitioners, decision-makers and academic researchers. When monitoring financial risk, the probability of a large adverse market movement is always of the great practical concern. Large market movements can occur due to market

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[1] Both Shares A and B are tradable shares. In addition, there is also a state share, which is not tradable.

[2] B-shares in SHSE are traded in U.S. dollars, and B-shares in SZSE are traded in Hong Kong dollars.

[3] We will not consider the N-share market because of the small number of Chinese firms listed in NYSE.

uncertainty, policy changes, surprising news or shocks, speculative attacks, and spillover from other markets (e.g., financial contagion). When they occur, extreme market movements imply changehands of a huge amount of capital among investors, leading to bankruptcy for some of them. They can even cause collapse of financial systems and social instability. Investors have been aware of painful experience when extreme adverse market movements occur.

Large market movements have become commonplace nowadays. For example, on the Black Monday, October 19, 1987, U.S. stocks collapsed by 23%, wiping out US$1 trillion in capital. Around 1990, Japanese stock prices fell, with the Nikkei 225 index sliding from 39,000 at the end of 1989 to 17,000 three years later, resulting in a total of US$ 2.7 trillions in capital loss. In the bond debacle of 1994, the U.S. Federal Reserve Broad, after having kept interest rates low for three years, started a series of six consecutive interest rate hikes that erased US$ 1.5 trillion in global capital. The U.S. Orange County Investment Pool, a portfolio of US$ 7.5 billion belonging to municipal investors, including the county, cities, and schools, lost US$ 1.64 billion in December, 1994. This is the largest municipal failure in history. During the 1997-1998 Asian financial crisis, several Asian currencies devaluated dramatically within a very short period (e.g., Woo *et al.* 2000). Other examples of large market movements include recent large price adverse movements in the U.S. stock market after the September 11 Terror Incident, the bankruptcies of the Long Term Capital Management, Enron, and Worldcom. In China, its stock market has been featured with overspeculative activity of massive individual investors, dramatic policy changes, and a huge amount of speculative capital, exhibiting excess market fluctuations. An example of extreme market movements in China is the sharp drop in Share B stock prices in 2001, due to the massive withdrawal of overseas investors after China opened Share B markets to domestic investors holding foreign currencies. Extreme market movements have had adverse impact on the steady development of Chinese stock market.

For effective financial risk management and investment/portfolio diversification, it is important to understand the mechanism of how risk spillover has occurred between different shares in Chinese stock market, and between Chinese stock market and overseas stock markets. When financial markets are completely segmented, risk cannot transmit across markets. This is exactly the reason why China could have escaped the Asian financial crisis during 1997-1998 (e.g., Lardy 1998). However, when markets are integrated and suffer from the same global shock, risk is expected to transmit across markets. Another possibility of risk spillover is the "market contagion", which can occur due to the attempts of investors to infer price changes in other markets. In this case, a large price change in one market may bring about a large price change in another market, regardless of the evolution of market fundamentals (e.g., King and Wadhwani 1990). It is also possible that risk in one market is generated locally or has characteristics specific to that market, but with the integration of markets, the risk will be transmitted into another market. For example, a domestically driven decline in Japanese stock price caused a decline in the wealth of Japanese stock holders, including Japanese banks. This decline reduced Japanese banks' capital and caused a decline in Japanese banking lending in the U.S. credit markets, given the regulations of Bank of International Settlements or BIS (Peek and Rosengren 1997). For another example, by the end of August 1997, as several Asian currencies devalued and stock markets in the Asian-Pacific area started to decline sharply, large institutional investors began selling off Chinese stocks in Hong Kong, leading to a shape decline of Share H prices.

Recent large financial disasters have called for the need of accurate risk measures for financial institutions and regulators. To monitor extreme risk and its spillover, it is crucial to quantify risk. In finance, volatility has been used as a standard quantitative measure for financial risk, particularly market risk. Markowitz's (1952) portfolio theory, for example, characterizes the trade-off between return and risk by using the mean and variance of asset returns. As the nature of financial risk has changed over time, the methods to measure risk must adopt to recent experience. In the fast paced financial world, effective risk measures must be responsive to news and must be easy to grasp even in complex situations. Sophisticated econometric models such as GARCH (Bollerslev 1986) and stochastic volatility (Taylor 1986) have been developed to capture volatility clustering. However, the variance measure includes, in a symmetric way, both gains and losses. It is a poor measure for occasionally occurring extreme risk. In practice, financial risk is obviously associated with losses but not profits. A definition of risk where both events play symmetric roles is not in conformity with the intuitive notion of risk. A sensible measure of risk should be associated with large losses, or large adverse market movements.

In statistics, left tail probabilities are closely related to the likelihoods of extreme events and the associated risk (e.g., Embrechts *et al.* 1997).[4] Although not a perfect measure of extreme market risk, Value at Risk (VaR), originally proposed by J.P. Morgan in 1994, has become a standard quantitative and synthetic measure of extreme market risk. It measures how much a certain portfolio can lose within a given time period, for a given confidence level. VaR has already become part of part of financial regulations (Basel Committee on Banking Supervision 1996, 2001) and has also been widely used in practice by financial institutions and regulators for setting risk capital requirements so as to ensure that financial institutions can survive after a catastrophic event (e.g., Duffie and Pan 1997 and Jorion 2000).[5] The great popularity that this instrument has achieved among financial practitioners is essentially due to its conceptual simplicity. The summary of many complex bad outcomes in a single monetary amount actually represents a compromise between the needs of different users.[6]

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[4] Probability theory has been widely used to describe movements of financial markets. A fundamental axiom behind is that financial market can be viewed as a stochastic data generating process, and financial data are realization of this data generating process. See Hong (2002) for more discussion.

[5] VaR is a measure of extreme downside risk and is similar in methodology to the method of lower partial moments in the earlier literature (e.g., Roy 1952).

[6] A more comprehensive risk measure will be the probability distribution function in combined with the in-

Using VaR as a measure of extreme downside market risk, Hong (2001b) recently introduced a new concept of Granger causality in risk, where a large risk is said to have occurred at a prespecified level if actual loss exceeds VaR at the given level. This concept is useful in investigating whether a large risk in one market will Granger-cause a large risk in another market. As is well-known, Granger causality (Granger 1969,1980) is not a relationship between "causes" and "effects". Instead, it is defined in terms of incremental predictive ability. This concept is thus suitable for the purpose of predicting and monitoring risk.

Applying a kernel-based approach to testing Granger causality in risk, we investigate extreme risk spillover between different shares in Chinese stock markets, and between Chinese stock market and overseas stock markets, the latter including those of Hong Kong, Taiwan, Singapore, South Korea, Japan, U.S. and Germany. Based on the daily stock indices from 1/2/1995 4/4/2003, we find some interesting empirical results: First, there exists strong risk spillover between Share A indices and Share B indices, and between SHSE and SZSE. Moreover, the occurrence of a large risk in Share B markets can help predict a similar future risk in Share A markets, but not vice versa. Second, there exists significant risk spillover between Mainland China stock market (particularly Shares B and H) and the stock markets in Hong Kong and Taiwan. Third, there exists some risk spillover between Chinese stock market (particularly Shares B and H) and the stock markets in South Korea and Singapore. Fourth, there exists no risk spillover between Share A indices and major international stock markets—those in Japan, U.S. and Germany. It appears that the price movement of Share A markets—the main constituent of Chinese stock market, is driven mainly by domestic factors, and its impact is at most regional. In particular, its interaction with international major capital markets is still weak or nonexistent in terms of large adverse market movements. Most extreme downside market risk spillover from international capital markets is absorbed in Share B markets and particularly Share H market. In terms of avoiding the impact of adverse large international market movements on Chinese stock market, the segmentation between Share A and Share B markets appears effective. Of course, this is expected to change given the recent policy changes of opening Share B markets to domestic investors and opening Share A markets to qualified foreign institutional investors.

In Section 2, we describe the concept of Granger causality in risk and discuss its relationship with the existing concepts of Granger causality in mean (Granger 1969), Granger causality in variance (Granger *at al.* 1986), and general Granger causality (Granger 1980). In Section 3, we describe a newly developed kernel-based approach to testing Granger causality in risk. Section 4 describes the data and reports summary statistics. In Section 5, we present estimation results and empirical findings, and discuss their implications. Section 6 concludes.

2. VALUE AT RISK AND GRANGER CAUSALITY IN RISK

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tertemporal utility maximization. See Hong (2002, Section 6) for more discussion.

2.1 Extreme Market Risk and Value at Risk

For a given time horizon τ and confidence level $1-\alpha$, VaR is the loss over the time horizon τ that is not exceeded with probability $1-\alpha$. Statistically speaking, VaR, denoted by $V_t \equiv V(I_{t-1}, \alpha)$ is the negative α-quantile of the conditional probability density function *(pdf)* of a time series (e.g., portfolio return) process Y_t which satisfies the following equation:

$$P\left(Y_t < -V_t | I_{t-1}\right) = \alpha, \tag{2.1}$$

where $I_{t-1} = \{Y_{t-1}, Y_{t-2}, ...\}$ is the information set available at time $t-1$. In financial risk management, the left tail probability in (2.1) is called the shortfall probability. For notational simplicity, we have suppressed the dependence of V_t on level α. Commonly used levels for α are 10%, 5% or 1%. For example, BIS sets $\alpha = 1\%$ and $\tau = 10$ days for purposes of measuring the adequacy of bank capital, J.P. Morgan discloses its daily VaR at the 5% level, and Bankers Trust discloses at the 1% level for its daily VaR. In economics and finance, economists have considered behavioral models of bank or insurance companies that maximize some utility criteria under a VaR-type solvency constraint (e.g., Gollier *et al.* 1996, Sentamero and Babbel 1996). There have been also studies on the optimal "safety-first" portfolio selection which, as an alternative to the traditional mean-variance efficient frontier, maximizes the expected return subject to a downside risk constraint (e.g., Roy 1952, Levy and Sarnet 1972, Arzac and Bawa 1977, Jansen *et al.* 1998). Some recent research (e.g., Ang *et al.* 2002) suggests that extreme downside risk can help explain asset returns.

To gain insight into VaR from a statistical perspective, we write the time series $\{Y_t\}$ as follows:

$$\begin{cases} Y_t &= \mu_t + \sigma_t \varepsilon_t, \\ \varepsilon_t &\sim \text{m.d.s.(0,1) with conditional CDF } F_t(\cdot), \end{cases} \tag{2.2}$$

where $\mu_t \equiv \mu(I_{t-1})$ and $\sigma_t^2 \equiv \sigma^2(I_{t-1})$ are the conditional mean and variance of Y_t given I_{t-1} respectively, and $F_t(\cdot) \equiv F(\cdot|I_{t-1})$ is the conditional cumulative distribution function (CDF) of ε_t given I_{t-1}. By definition, the standardized innovation $\{\varepsilon_t\}$ is a conditionally homoskedastic martingale difference sequence (m.d.s.) with $E(\varepsilon_t|I_{t-1}) = 0$ a.s. and $\text{var}(\varepsilon_t|I_{t-1}) = 1$ a.s. From (2.1) and (2.2), we can obtain the VaR

$$V_t = -\mu_t + \sigma_t z_t(\alpha), \tag{2.3}$$

where $z_t(\alpha) \equiv z(I_{t-1}, \alpha)$ is the left-tailed critical value at level α of the conditional distribution $F_t(\cdot)$ of ε_t; that is, $z_t(\alpha)$ satisfies $F_t[z_t(\alpha)] = \alpha$. Obviously, V_t depends on not only the conditional mean μ_t and variance σ_t^2 of Y_t, but also its higher order conditional moments (e.g., skewness and kurtosis). In (2.2), Y_t is not covariance-stationary if σ_t^2 follows an integrated GARCH (IGARCH) process (Engle and Bollerslev 1986). In this case, the unconditional variance of $\{Y_t\}$ does not exist, but its VaR is still well-defined.

In practice, a most popular model for VaR is J.P. Morgan's (1997) RiskMetrics:

$$\begin{cases} Y_t & = \sigma_t \varepsilon_t, \\ \sigma_t^2 & = (1-\lambda) \sum_{j=1}^{\infty} \lambda^j Y_{t-j}^2, \\ \varepsilon_t & \sim \text{ i.i.d. N(0,1)}, \end{cases} \tag{2.4}$$

where the parameter λ governs the dependence of the current volatility on its past history. For daily financial series, J.P. Morgan suggests $\lambda = 0.94$. Under (2.4), the VaR is

$$V_t = \sigma_t z(\alpha), \tag{2.5}$$

where $z(\alpha)$ is the one-sided N(0,1) critical value at level α. For example, $z(\alpha) = 1.28, 1.65$ and 2.33 for $\alpha = 0.10, 0.05$ and 0.01 respectively. Clearly, the higher the expected volatility σ_t^2, the larger the VaR.

2.2 Granger Causality in Risk

Because VaR is a threshold measure for extreme downside risk, we may say that a large downside risk has occurred if actual loss exceeds VaR. In practice, financial institutions and regulators are seriously concerned with the probability of such a risk, which is very rare but may cause financial disaster if it occurs. The concept of Granger causality in risk was proposed to test whether the occurrence of a large risk in one market (Y_{1t}) will cause the occurrence of a large risk in another market (Y_{2t}) in the spirit of Granger (1969,1980) causality. Put $I_{t-1} \equiv (I_{1(t-1)}, I_{2(t-1)})$, where $I_{1(t-1)} = \{Y_{1t-1}, ..., Y_{11}\}$ and $I_{2(t-1)} = \{Y_{2t-1}, ..., Y_{21}\}$ are the information sets available at time $t-1$ for market 1 and 2 respectively. Suppose

$$\mathbb{H}_0 : P\left(Y_{1t} < -V_{1t} | I_{1(t-1)}\right) = P\left(Y_{1t} < -V_{1t} | I_{t-1}\right) \text{ almost surely } (a.s.), \tag{2.6}$$

we say that the time series $\{Y_{2t}\}$ *does not* Granger-cause the time series $\{Y_{1t}\}$ in risk at level α with respect to information set I_{t-1}. On the other hand, if

$$\mathbb{H}_A : P\left(Y_{1t} < -V_{1t} | I_{1(t-1)}\right) \neq P\left(Y_{1t} < -V_{1t} | I_{t-1}\right). \tag{2.7}$$

we say that the time series $\{Y_{2t}\}$ Granger-causes the time series $\{Y_{1t}\}$ in risk at level α with respect to I_{t-1}. In this case, the information of the occurrence of a risk in $\{Y_{1t}\}$ can be used to predict possible occurrence of a future risk in $\{Y_{2t}\}$. In practice, level α can be determined by regulators or practitioners, depending on their objective function.

In time series econometrics, the most commonly used Granger causality concept is Granger causality in mean, which was first introduced in Granger (1969). Granger *et al.* (1986, p.2) also introduce a concept of Granger causality in variance, which can be used to investigate volatility spillover across financial markets (cf. Engle *et al.* 1990). Here, the concept of Granger causality in risk focuses on the comovement between the left tail distributions, which is more suitable than the concept of Granger causality in variance for characterizing extreme downside risk spillover between different markets, because, as noted earlier, volatility is a two-sided risk measure. We note that Granger causality in risk can arise not only from comovements in mean and in variance, but also from the comovements in higher order conditional moments (e.g., skewness and kurtosis). In other words, Granger causality in risk may rise even in the absence of Granger causality in mean and in variance.

Granger (1980) introduces a general Granger causality in terms of the entire conditional probability distribution $P(Y_{1t} \leq y|I_{1(t-1)}) \neq P(Y_{1t} \leq y|I_{t-1})$ for all $y \in (-\infty, \infty)$. Our concept of Granger causality in risk is more closely related to this general Granger causality, but again we only focus on left tail probabilities, which are more relevant to large downside market risk.

3. METHOD TO TEST GRANGER CAUSALITY IN RISK

We now describe a recently proposed kernel-based test for Granger causality in risk. Define a VaR-based "risk indicator"

$$Z_{lt} \equiv \mathbf{1}\left(Y_{lt} < -V_{lt}\right), \quad l = 1, 2. \tag{3.1}$$

where $\mathbf{1}(\cdot)$ is the indicator function. This risk indicator takes value 1 when actual loss exceeds VaR, and takes value 0 otherwise. The hypotheses $\mathbb{H}_0$ and $\mathbb{H}_A$ can be equivalently stated as

$$\mathbb{H}_0 : E\left(Z_{1t}|I_{1(t-1)}\right) = E\left(Z_{1t}|I_{t-1}\right) \; a.s.$$

versus

$$\mathbb{H}_A : E\left(Z_{1t}|I_{1(t-1)}\right) \neq E\left(Z_{1t}|I_{t-1}\right).$$

Thus, Granger causality in risk between $\{Y_{1t}\}$ and $\{Y_{2t}\}$ can be viewed as Granger causality in mean between $\{Z_{1t}\}$ and $\{Z_{2t}\}$.

One important implication of non-Granger causality in risk ($\mathbb{H}_0$) is:

$$\text{cov}(Z_{1t}, Z_{2t-j}) = 0 \text{ for all lags } j > 0.$$

Thus, if $\text{cov}(Z_{1t}, Z_{2t-j}) \neq 0$ for some lag $j > 0$, then there exists evidence of Granger causality in risk. In particular, it implies that if a large risk has occurred in one market, we can use this information to predict possible occurrence of a large future risk in another market. We could of course use other information in I_{2t-1} to predict a risk in Y_{1t}. However, the main purpose of this paper is to investigate extreme downside risk spillover between different markets, so the use of $\text{cov}(Z_{1t}, Z_{2t-j})$ is appropriate.

Now suppose

$$V_{lt}(\theta_l) \equiv V_l(I_{l(t-1)}, \theta_l, \alpha), \quad l = 1, 2, \tag{3.2}$$

is a VaR model for V_{lt} at level α, where θ_l is an unknown model parameter that has to be estimated from historical data. There have been many methods to estimate VaR (e.g., Jorion

2000). Examples are historical simulation methods, J.P. Morgan's RiskMetrics, and Engle and Manganlli's (1999) conditional autoregressive VaR (CAViaR) models. In our empirical analysis below, we will use a GARCH modeling approach that is more sophisticated than J.P. Morgan's RiskMetrics.

Suppose we have a random sample $\{Y_{1t}, Y_{2t}\}_{t=1}^{T}$ of size T, and an estimator $(\hat{\theta}_1, \hat{\theta}_2)$. Put

$$\hat{Z}_{lt} \equiv \mathbf{1}[Y_{lt} < -V_{lt}(\theta_l)], \quad l = 1, 2. \tag{3.3}$$

Then we can define the sample cross-covariance function between $\{\hat{Z}_{1t}\}$ and $\{\hat{Z}_{2t}\}$,

$$\hat{C}(j) \equiv \begin{cases} T^{-1}\sum_{t=1+j}^{T}(\hat{Z}_{1t} - \hat{\alpha}_1)(\hat{Z}_{2t-j} - \hat{\alpha}_2), & 0 \leq j \leq T-1, \\ T^{-1}\sum_{t=1-j}^{T}(\hat{Z}_{1t+j} - \hat{\alpha}_1)(\hat{Z}_{2t} - \hat{\alpha}_2), & 1-T \leq j < 0, \end{cases} \tag{3.4}$$

where $\hat{\alpha}_l \equiv T^{-1}\sum_{t=1}^{T}\hat{Z}_{lt}$. The sample cross-correlation function between $\{\hat{Z}_{1t}\}$ and $\{\hat{Z}_{2t}\}$ is

$$\hat{\rho}(j) \equiv \hat{C}(j)/\hat{S}_1\hat{S}_2,, \quad j = 0, \pm 1, ..., \pm(T-1), \tag{3.5}$$

where $\hat{S}_l^2 \equiv \hat{\alpha}_l(1-\hat{\alpha}_l)$ is the sample variance of $\{\hat{Z}_{lt}\}$. We could replace $\hat{\alpha}_l$ with α.

Following Hong's (2001b) approach to testing Granger causality in variance, a kernel-based portmanteau test for Granger causality in risk can be proposed:

$$Q_1(M) = \left\{T\sum_{j=1}^{T-1}k^2(j/M)\hat{\rho}^2(j) - C_{1T}(M)\right\} / \left\{2D_{1T}(M)\right\}^{1/2}, \tag{3.6}$$

where the centering and scaling factors [7]

$$\begin{aligned} C_{1T}(M) &= \sum_{j=1}^{T-1}(1-j/T)k^2(j/M), \\ D_{1T}(M) &= \sum_{j=1}^{T-2}(1-j/T)\left\{1-(j+1)/T\right\}k^4(j/M). \end{aligned}$$

Here, the weighting function $k(\cdot)$ is called a kernel. It can have bounded or unbounded support. An example of $k(\cdot)$ with bounded support is the Bartlett kernel $k(z) = (1-|z|)\mathbf{1}(|z| \leq 1)$, and an example of $k(\cdot)$ with unbounded support is the Daniell kernel $k(z) = \sin(\pi z)/\pi z$. When $k(\cdot)$ has a bounded support, M is a lag truncation order. When $k(\cdot)$ has an unbounded support, M is no longer a lag truncation order, because all $T-1$ sample cross-correlations are used; in this case we can view M as an effective lag truncation order. Most commonly used kernels discount higher order lags. Extending the proof of Hong (2001a), we can show that under certain regularity conditions (including $M \to \infty, M/T \to 0$ as $T \to \infty$), $Q_1(M) \to N(0,1)$ in distribution under $\mathbb{H}_0$.

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[7] For large M, we can approximate $C_{1T}(M)$ and $D_{1T}(M)$ by $MC_{1T}(M) = M\int_0^{\infty}k^2(z)dz$ and $MD_{1T}(M) = M\int_0^{\infty}k^4(z)dz$ respectively.

The $Q_1(M)$ test has two appealing features. First, it checks an increasing number of lags ($M \to \infty$) as sample size T grows. This ensures power against a wide range of alternatives. In practice, it is possible that there exists a time delay in risk spillover, because investors may need some time to interpret and digest news, particularly bad news. As a result, the first several lags will have zero cross-correlation. It is also possible that the cross-correlation at each lag is very small, but it carries over a long distributional lag and the cumulative effect all together is strong. The $Q_1(M)$ test with a large M is expected to be powerful against these processes.

Usually when a larger number of lags is used, the power of a test will suffer from the loss of a large number of degrees of freedom, such as many chi-square tests in time series analysis (e.g., Box and Pierre's 1971 portmanteau test). Fortunately this is not the case of the $Q_1(M)$ test, because the weight $k^2(j/p)$ discounts higher order lags. Downward weighting is consistent with the stylized fact that financial markets are often more influenced by the recent events than by the remote past events, and therefore it will enhance good power of the test. Indeed, it can be shown that over a class of non-uniform kernel functions, the Daniell kernel maximizes the power of $Q_1(M)$ (see Hong 1996 for more discussion).

Whenever $\rho(h) \neq 0$ for some $h > 0$, $Q_1(M)$ will diverge to positive infinity as T grows. Thus, upper-tailed $N(0,1)$ critical values should be used. For example, the asymptotic critical value at the 5% significance level is 1.645.

One may also be interested in testing whether there exists risk spillover, including instantaneous one, between two markets. The null hypothesis is that neither market Granger causes the other in risk and there exists no instantaneous risk spillover between the two markets. This implies $\mathrm{cov}(Z_{1t}, Z_{2t-j}) = 0$ for all $j = 0, \pm 1, \pm 2, \ldots$. To test this hypothesis, we can use the following test statistic

$$Q_2(M) = \left\{ T \sum_{j=1-T}^{T-1} k^2(j/M)\hat{\rho}^2(j) - C_{2T}(M) \right\} / \left\{2D_{2T}(M)\right\}^{1/2}, \qquad (3.7)$$

where the centering and scaling factors

$$\begin{aligned} C_{2T}(M) &= \sum_{j=1-T}^{T-1} (1 - j/T)k^2(j/M), \\ D_{2T}(M) &= \sum_{j=2-T}^{T-2} (1 - j/T)\left\{1 - (j+1)/T\right\} k^4(j/M). \end{aligned}$$

Like $Q_1(M)$, $Q_2(M)$ also has a null asymptotic N(0,1) distribution. For convenience, we will call $Q_1(M)$ the test for one-way Granger causality in risk, and $Q_2(M)$ the test for two-way Granger causality in risk.

4. DATA

We now use the $Q_1(M)$ and $Q_2(M)$ tests to investigate risk spillover between Chinese stock market and overseas capital markets. We will consider twelve stock price indices in Chinese stock market and those of Hong Kong, Taiwan, Singapore, South Korea, Japan, U.S. and Germany. These indices are Shanghai A Share Index (SHA), Shanghai B Share Index (SHB), Shenzhen A Share Subindex (SZA), Shenzhen B Share Subindex (SZB), Hong Kong Hang Seng China Enterprises Index (HKH, or Share H), Hong Kong Hang Seng Index (HSI), Taiwan Weighted Index (TWI), Singapore Straits Times Index (STI), South Korea Composite Index (KOSPI), Japan Nikkei 225 Index (NK225), U.S. S&P 500 Composite Index (S&P500) and German DAX 30 Index (DAX). To avoid the abnormal price fluctuations of the Chinese stock market a few months after 8/1/1994, during which stock price movements were mainly driven by dramatic policy changes, we select our sample from 1/2/1995 to 4/4/2003. The data are daily closing prices, with SHA, SHB, SZA and SZB obtained from SHSE and all the other from Datastream.

Figures 1 and 2 plot the daily series of the twelve stock price indices and their changes defined in terms of log-difference scaled by 100. Figure 1 shows that SHA and SZA follow a similar pattern, so do SHB and SZB. However, Share A indices and Share B indices have different patterns of price dynamics. Also, Share A indices and Share B indices exhibit different patterns from Share H and HSI. On the other hand, TWI, STI and KOSPI show similar price movements, S&P 500 and DAX have similar trends. Except Chinese A Share indices, all the other indices of Asian stock market experience a steep fall in the middle of 1997. Figure 2 shows that there exists rather strong volatility clustering in all stock indices. For Chinese stock market, SHA and SZA have a similar volatility clustering pattern, so do SHB and SZB. However, Share A indices and Share B indices have different volatility clustering patterns. For Share A indices, there were more variations in the early stage of the sample than in the later stage. This is perhaps due to the implementation of a 10% band limit on daily stock price changes with a $T+1$ settlement rule after 12/16/1996. In contrast, for Share B indices, there were more variations in the later stage of the sample than in the early stage. This indicates the booming of Share B markets, which might be due to the introduction of a legal regulation in 01/1996 to encourage foreign investment in Share B markets and to open Share B markets to domestic investors in 02/2001.

Table 1 reports some summary statistics—sample mean, variance, skewness and kurtosis of each daily stock price change series. SHA, SZA, SHB, SZB, S&P500 and DAX all have positive average returns. Except HSI, all other Asian stock indices have negative average returns. It is clear that the Chinese stock market (except Share H) offers higher average return than other stock markets, with relatively higher standard deviation at the same time. This to some extent indicates that Chinese stock market, as an emerging capital market, is more volatile than developed stock markets in the world. HKH has the largest standard deviation among all indices, but the average return is negative. We also note that the long-term performance of Share B markets lags far behind Share A markets, however, Share B have higher standard deviation. Compared with Shenzhen market, Shanghai market has a smaller standard deviation. On the other hand, the Chinese stock indices all have positive skewness, with SHA having the largest skewness. Most of the other stock indices have negative skewness. All stock indices have a kurtosis larger than 3, indicating non-Gaussian features of stock price changes. SHA and SZA have a largest kurtosis among all indices.

5. EMPIRICAL ANALYSIS

5.1 Model Estimation

Let P_t be the price of a stock index at time t. We define the daily stock price change at time t as follows:

$$Y_t = 100 \ln(P_t/P_{t-1}). \tag{5.1}$$

To account for persistent volatility clustering and possible weak serial dependence in Y_t, we specify an AR(m) model with Threshold GARCH (TGARCH) errors:

$$\begin{cases} Y_t = & b_0 + \sum\limits_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t, \\ \varepsilon_t = & \xi_t h_t^{1/2}, \ \xi_t \sim \ \text{i.i.d.N(0,1)}, \\ h_t = & \omega + \sum\limits_{k=1}^{n} \alpha_k h_{t-k} + \beta_1 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} > 0) + \beta_2 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} \leq 0). \end{cases} \tag{5.2}$$

In the empirical finance literature, it is often found that GARCH(1,1) and GARCH(2,1) models can capture most volatility clustering of financial time series (e.g., Engle 1986, 1993). We use TGARCH models to capture the “leverage effects”. For all stock indices, we first consider an AR(3)-TGARCH(1,1) model. If diagnostic checking shows that the model is not adequate, we then try models with a higher order AR and a higher order TGARCH. This is the so-called “from specific-to-general”modeling approach. Table 2(a,b) reports the maximum likelihood estimation of univariate AR-TGARCH models for all indices. For SHA, SZB, HSI, STI, KOSPI, NK225 and DAX, diagnostic checking (reported in Table 2) indicates that an AR(3)-TGARCH(1,1) model is adequate. For SZA, an AR(4)-TGARCH(2,1) model is adequate. For HKH, an AR(3)-TGARCH(2,1) model is adequate, and for TWI, an AR(4)-TGARCH(1,1) model is adequate.

Among all indices, SHB and S&P 500 are most specific. Figure 2(a) reveals the SHB volatility becomes larger from late 1996. To capture this potential structural change, we introduce two time dummy variables for the intercepts in mean and in variance respectively. Hence, the model for SHB is specified as the follows:

$$\begin{cases} Y_t = & b_0 + d_1 \mathbf{1}(t > 500) + \sum\limits_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t, \\ \varepsilon_t = & \xi_t h_t^{1/2}, \ \xi_t \sim \ \text{i.i.d.N(0,1)}, \\ h_t = & \omega + d_2 \mathbf{1}(t > 500) + \sum\limits_{k=1}^{n} \alpha_k h_{t-k} + \beta_1 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} > 0) + \beta_2 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} \leq 0). \end{cases} \tag{5.3}$$

For S&P500, the estimate of β_1 in model (5.2) is almost zero, so we use the following standard AR(3)-GARCH(1,1) model:

$$\begin{cases} Y_t = & b_0 + \sum_{j=1}^{3} b_j Y_{t-j} + \varepsilon_t, \\ \varepsilon_t = & \xi_t h_t^{1/2},\ \xi_t \sim \text{ i.i.d.N(0,1)}, \\ h_t = & \omega + \alpha_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2. \end{cases} \tag{5.4}$$

Table 2 shows that not all parameter estimates are significant at the 5% significance level, but TGARCH parameters $(\hat{\alpha_1}, \hat{\alpha_2}, \hat{\beta}_1, \hat{\beta}_2)$ are highly significant, with $\hat{\beta}_2 > \hat{\beta}_1$, which confirms the existence of "leverage effects". For SHB, the variance dummy coefficient estimate $\hat{d}_2$ is significant at the 1% significance level. This is consistent with the SHB volatility pattern displayed in Figure 2(a). Table 2 also reports some diagnostic statistics for model adequacy. The p-values of a generalized Box and Pierce's (1971) type portmanteau statistic for autocorrelation in standardized residuals $\{\hat{\varepsilon}_t/\hat{\sigma}_t\}$ are all well above 0.10, so are the p-values of a similar test for autocorrelation in squared standardized residuals $\{\hat{\varepsilon}_t^2/\hat{\sigma}_t^2\}$. These results indicate the adequacy of the specified models for each index.

5.2 Evidence on Granger Causality in Risk

5.2.1 Risk Spillover Among the Chinese Stock Markets

We first investigate risk spillover between SHA, SHB, SZA, SZB, and HKH (Share H), which constitute a comprehensive picture of the Chinese stock market.

Table 3(a,b) reports test statistics for Granger causality in risk at $\alpha = 10\%$ and $\alpha = 5\%$ levels, together with their p-values. Because commonly used non-uniform kernels deliver similar results, we only report the results based on the Daniell kernel. For the 10% and 5% risk levels, we find extremely significant evidence on two-way Granger causality in risk between SHA and SZA, and between SHB and SZB respectively, suggesting strong risk spillover between SHSE and SZSE. In order to identify the direction of risk spillover, we also report test statistics for one-way Granger causality in risk between SHA and SZA, and between SHB and SZB. At the 10% risk level, we find that SHA Granger-causes SZA in risk with respect to I_{t-1} and vice versa. At the 5% risk level, we find significant Granger causality in risk from SZA to SHA with respect to I_{t-1}, but there exists only marginally significant evidence on Granger-causality in risk from SHA to SZA with respect to I_{t-1}. On the other hand, there exists significant evidence that SHB Granger-causes SZB in risk and vice versa at the two risk levels.

Next, we consider risk spillover between: (i) SHA and SHB, (ii) SHA and SZB, (iii) SZA and SHB, (iv) SZA and SZB respectively. We find extremely significant two-way Granger causality in risk between Share A and Share B. This finding is hardly surprising, because Share A and Share B are the prices of the same company in two different markets; they have some common driving forces for price dynamics despite market segmentation. Interestingly, one-way Granger causality test statistics show that Share B Granger-causes Share A in risk at the 10% risk level, but not vice versa. This might be because Share B prices are more sensitive to the fundamentals of profitability of the listed companies and are not likely to be influenced by Share A prices when price changes are large. From the asymmetric point of view, it seems that the investors in Share B markets are better informed, which may also be a reflection that foreign investors are better informed than Chinese domestic investors in the Share A markets. It challenges a widespread assumption in the finance literature that foreign investors are less informed than domestic investors (Stulz and Wasserfallen 1995, Kang and Stulz 1996, Brennan and Cao 1997), but in line with the arguments of some researchers (Chui and Kwok, 1998, Mok and Hui 1998) and consistent with more recent research (Froot and Seasholes 2001, Chan and Wright 2001) that foreign investors portfolio inflows have noticeable ability to predict positive future returns in emerging markets. The story is a bit different at the 5% risk level: we only find instantaneous risk spillover between SZB and SZA/SHA.

Finally, we consider risk spillover between Shares A/B and Share H. At the 10% level, tests of two-way Granger causality in risk show strong risk spillover between Share A and Share H, and tests of one-way Granger causality in risk show that Share H Granger causes Share A in risk. We also find that SZA (but not SHA) Granger causes Share H. At the 5% risk level, there is no risk spillover between SZA and HKH, but for large M, we find significant evidence that Share H Granger-causes SHA in risk with respect to I_{t-1}. It is possible that there exists a time delay in risk spillover or risk spillover carries over a very long distributional lag from Share H to SHA.

Tests for two-way Granger causality in risk show that there exists significant risk spillover between Share B and Share H at the two risk levels. Moreover, tests of one-way Granger causality in risk indicates that SHB and SZB Granger-causes HKH in risk and vice versa at the 10% risk levels.

To summarize our findings: (1) There exists strong risk spillover between Share A and Share B, and between SHSE and SZSE. Moreover, Share B Granger causes Share A in risk but not vice versa at the 10% risk level. (2) There exists significant risk spillover between Share A and Share H, and between Share B and Share H. The latter is stronger than the former. (3) Risk spillover is more significant at the 10% risk level than at the 5% risk level.

The existence of strong risk spillover between Share A and Share B is possibly due to the fact that both markets are influenced by domestic policy changes, government's intervention, and macroeconomic factors in China. On the other hand, Share B and Share H are both traded in foreign currencies and were restricted to foreigners before 2001. Both markets are affected by foreign investors' sentiment toward Chinese economy and international shocks. As a consequence, risk spillover between Share B and Share H is stronger than Share A and Share H.

5.2.2 Risk Spillover Among Greater China

Economically, Mainland China, Hong Kong and Taiwan constitute Greater China area. Panel A of Table 4 reports test statistics (with p-values) for Granger causality in risk between the

Chinese stock market and Hong Kong Hang Seng Index (HSI). At the 10% and 5% risk levels, we find significant Granger causality in risk from Share A to HSI with respect to I_{t-1}, but we find no evidence that HSI Granger causes Share A indices in risk. On the other hand, tests of two-way Granger causality in risk indicates strong risk spillover between Share B indices and HSI at both the 10% and 5% risk levels. Moreover, tests of one-way Granger causality in risk show that SHB Granger causes HSI in risk with respect to I_{t-1}, and HSI Granger causes to SZB in risk with respect to I_{t-1}. These results are perhaps due to the fact that SHB is traded in U.S. dollars, and SZB is traded in Hong Kong dollars. On the other hand, tests of two-way Granger causality in risk show strong risk spillover between HKH and HSI at both the 10% and 5% levels. At the 10% risk level, tests of one-way Granger causality in risk show that HKH Granger-causes HSI in risk and vice versa with respect to I_{t-1}. At the 5% level, there is only instantaneous risk spillover between HKH and HSI. We note that risk spillover between Shares B/H and HSI is stronger than risk spillover between Share A and HSI. In all, we can find that the the downside movements of SHA, SZA and SHB all have a significant predictive power for the price fall of HSI, and the occurrence of a large risk in HSI help predict a similar future risk in SZB.

Panel B of Table 4 reports test statistics for Granger causality in risk between Mainland China stock market and Taiwan stock market. There is no risk spillover between SHA and TWI, but SZA Granger-causes TWI in risk and vice versa with respect to I_{t-1} at the 5% risk level. This is perhaps because most companies listed in SZSE are joint-ventures and foreign-trade oriented, while the majority of listed companies in SHSE are state-owned enterprises. For Share B indices and TWI, we find that TWI Granger-causes SHB in risk at the 10% risk level, but at the 5% level, there exists only instantaneous risk spillover between SHB and TWI. We also find that TWI Granger causes SZB in risk at the 10% risk level, but at the 5% level, there is no spillover between them. Finally, tests of one-way Granger causality in risk indicates strong risk spillover from Share H to TWI.

To sum up, we find that the three different shares—A, B and H in Chinese market have significant risk spillover with Hong Kong and Taiwan stock markets. This finding is consistent with the stylized fact that Mainland China, Hong Kong and Taiwan have geographical proximity and close economic ties.

5.2.3 Risk Spillover Between Chinese Stock Market and Asian Stock Markets

Singapore and South Korea, two newly industrialized economies in East Asia, and Japan, one of the most highly developed economies in the world, are representative of Asian countries. We now consider risk spillover between Chinese stock market and these Asian capital markets.

Panel A of Table 6 reports test statistics (with p-values) for risk spillover between Chinese stock market and Singapore stock market. We find a very little risk spillover between Share A indices and STI, but there exist significant risk spillover between Share B indices and STI at both the 10% and 5% risk levels. For HKH and STI, tests of two-way Granger causality in risk reveal strong risk spillover between Share H and STI at the two risk levels. Tests of one-way Granger causality in risk suggests that HKH Granger-causes STI in risk and vice versa at the 10% risk level, but at the 5% risk level, we only find that STI Granger-causes HKH in risk with respect to I_{t-1}.

Panel B of Table 6 reports results for Granger causality in risk between Chinese stock market and South Korean stock market. There exists significant risk spillover between Share A indices and KOSPI, and between Share B indices and KOSPI. Tests of two-way Granger causality in risk suggest strong risk spillover between HKH and KOSPI. And tests of one-way Granger causality in risk show that HKH Granger-causes KOSPI in risk and vice versa. Interestingly, a comparison between Panels A and B shows that risk spillover between Chinese stock market and Korea stock market is stronger than risk spillover between Chinese stock market and Singapore stock market. This might be due to the stronger economic link between China and South Korea. As two major economies in Asian, trade and direct investment between the two countries have expanded rapidly. According to South Korean statistics, South Korea's trade with China reached US$41.2 billion in 2002, making China the third largest trade partner of South Korea. Meanwhile, South Korea's direct investment in China totaled $1.72 billion during the same year. This constitutes 34 percent of South Korea's total outward foreign direct investment.

Panel C of Table 6 reports test statistics for Granger causality between Chinese stock and Japan stock market. There is no evidence on risk spillover between Share A indices and NK225. However, at the 5% risk level, tests of two-way Granger causality in risk show significant risk spillover between Share B indices and NK225. Because all one-way Granger causality in risk between Share B indices and NK225 are insignificant, we may conclude that there is only instantaneous risk spillover between Share B indices and NK225 at the 5% risk level. At the 10% risk level, there exists instantaneous risk spillover between SZB and NK225, but there is no evidence on risk spillover between SHB and NK225. Finally, there exists strong instantaneous risk spillover between HKH and NK225 at both the 10% and 5% risk levels.

5.2.4 Risk Spillover Between Chinese Stock Market and International Stock Markets

As is well-known, U.S. is the largest and most powerful economy in the world, and Germany is an advanced market economy and a world leader in export. Their stock markets are most representative of major international markets. We now investigate risk spillover between Chinese stock market with these two mature capital markets.

Panels A and B of Table 7 report test statistics for Granger causality in risk between Chinese stock market and U.S. and German stock markets. Both tests of two-way and one-way Granger causality in risk suggest that there is no risk spillover between Share A indices and S&P500/DAX. However, there exists significant risk spillover between Share B indices and S&P500/DAX. There is even stronger risk spillover between Share H and S&P500/DAX. We should note that there are time lags between the opening hours of Chinese stock market and U.S. and German stock markets; care must be taken when one interprets the above empirical results.

To summarize, we have the following observations:

1. There exists strong risk spillover between Share A and Share B, and between SHSE and SZSE. Moreover, Share B Granger causes Share A in risk with respect to I_{t-1} at the 10% risk level, but not vice versa.
2. There exists strong risk spillover between Shares A/B and Share H. Risk spillover between Share B and Share H is stronger than the risk spillover between Share A and Share H.
3. There exists significant risk spillover between Mainland China stock market (particularly Shares B and H) and Hong Kong and Taiwan's stock markets.
4. There exists some risk spillover between Chinese stock market (particularly Shares B and H) and Singapore stock market and between Chinese stock market and South Korean stock market. The latter is stronger than the former.
5. There is no evidence on risk spillover between Share A indices and major international stock markets–Japan, U.S. and Germany. However, there exists risk spillover between Shares B/H and these international stock markets.
6. Among the three shares–A, B and H in Chinese stock market, risk spillover between Share H and overseas capital markets is the strongest, and risk spillover between Share A and overseas capital markets is the weakest or nonexistent.

The finding that Share A markets have little risk spillover with leading international capital markets is possibly due to the fact that the price movement of share A markets is largely driven by domestic policy changes and government's market intervention. It is largely uncorrelated with the listed companies' fundamental profitability and is expected to be insulated from global financial market turbulence given market segmentation and invertibility of Chinese currency. On the other hand, Shares B and H are both traded by foreign investors with different investment opportunities. Both markets are affected by foreign investors' sentiment toward Chinese economy. They are influenced by global market climates and the fundamental profitability of the listed Chinese companies, in addition to domestic policy changes in China. However, there is a difference: Share B markets are traded in China's domestic exchanges by offshore investors before 2001 and suffered from lack of liquidity from the beginning. Share H markets are traded in Hong Kong where there are a higher liquidity, more institutional investors, more disclosure, and better communications with shareholders. Consequently, Share H market has been associated with tremendous market volatility and has more mutual interaction with international capital markets than Share B markets.

6. CONCLUSION

Monitoring extreme downside market risk is important for investment/portfolio diversification and risk management. In this paper, we have provided probably the first empirical study on spillover of extreme downside market risk between Shares A, B and H in Chinese stock market, between different stock markets in Greater China, and between Chinese stock market and international capital markets. It is found that there exists strong risk spillover between Share A indices and Share B indices, and the occurrence of a large downside risk in Share B markets can help predict the occurrence of a similar future risk in Share A markets. There also exist strong risk spillover between Share A and Share H, and particularly between Share B and Share H. Share B, and particularly Share H, have significant risk spillover with Asian and international stock markets. In contrast, although Share A has some risk spillover with Korean and Singapore stock markets, it has no risk spillover with leading international mature capital markets—Japan, U.S. and Germany. These findings suggest that the market segmentation between Share A and Share B is effective in avoiding large adverse shocks from international capital markets in terms of large adverse market movements. Chinese stock market has close tie with Asian stock markets, but its link with leading international capital markets is still weak or nonexistent.

However, the segmentation between Share A and Share B markets —originally restricted for local and foreign investors respectively, has blurred in recent years. Domestic investors have been allowed to invest in Share B markets since about two years before. At the end of last year, China decided to open Share A markets to qualified foreign institutional investors.[8] These reforms, together with more and more Chinese companies listed in oversea stock markets, will bring the Chinese stock markets closer to international capital markets. It is conceivable that relatively weak risk spillover between Share A markets and international stock markets will become stronger, but this remains to be verified when a sufficiently amount of data becomes available as time goes. Our approach and results can be useful for further empirical study along this avenue.

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[8] Four major international institutional investors, UBS AG of Switzerland, Japan's Nomura Securities, Morgan Stanley, and Citigroup, have been recently approved for entering the Share A markets.

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Figure 1(a): Daily Stock Price Indices

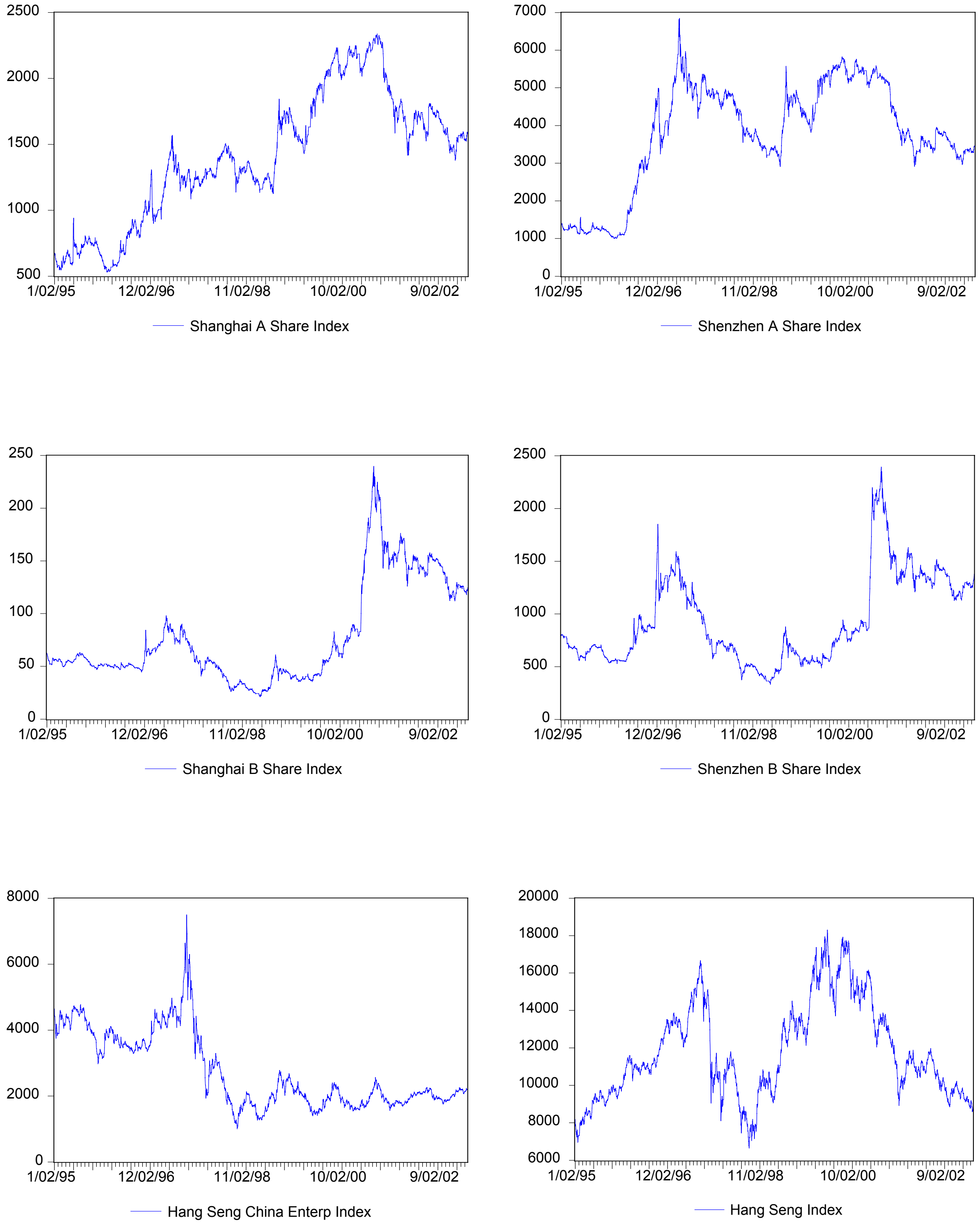
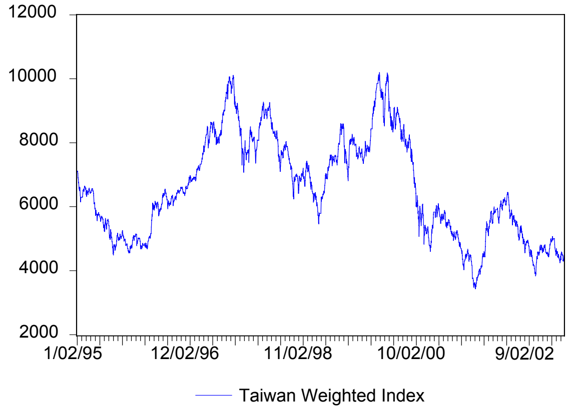
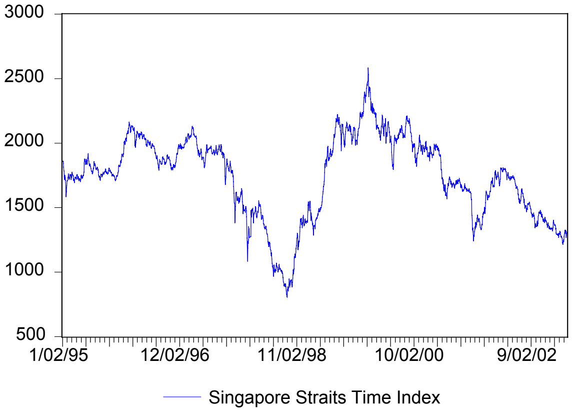
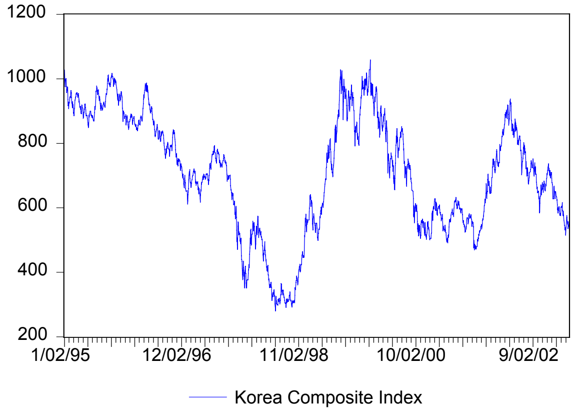
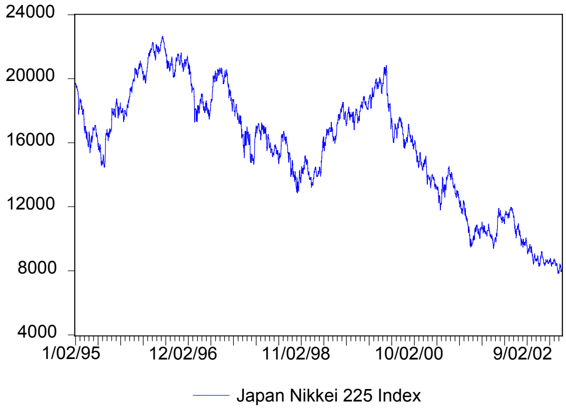


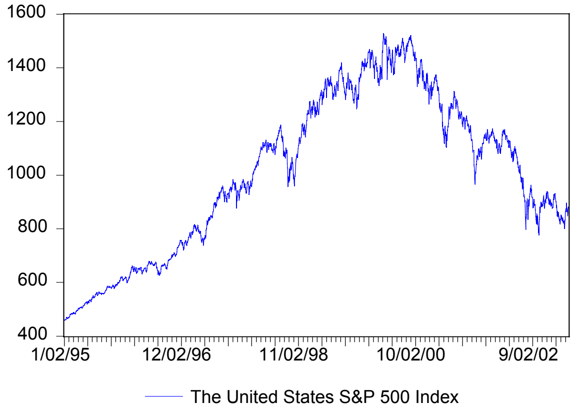
Figure 1(b): Daily Stock Price Indices











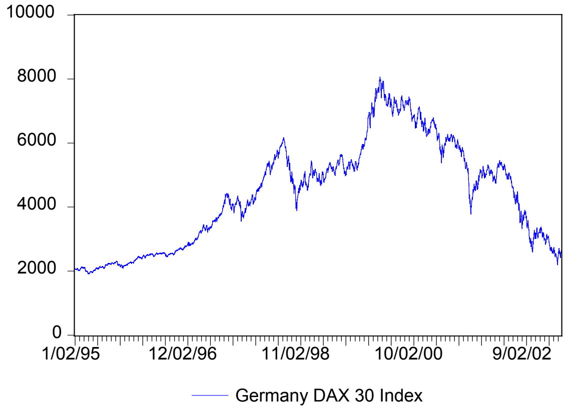


Figure 2(a): Daily Stock Price Changes

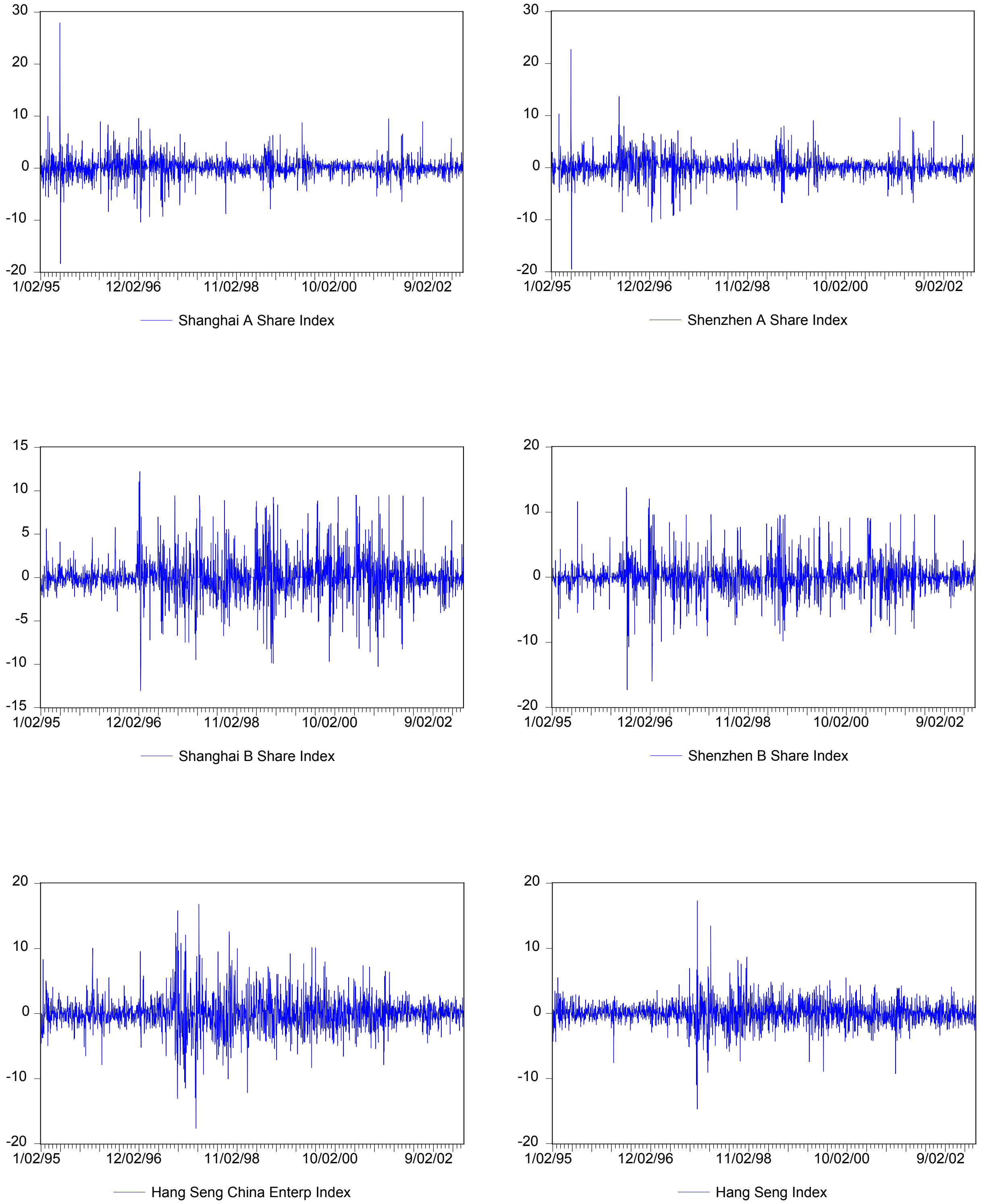


Figure 2(b): Daily Stock Price Changes

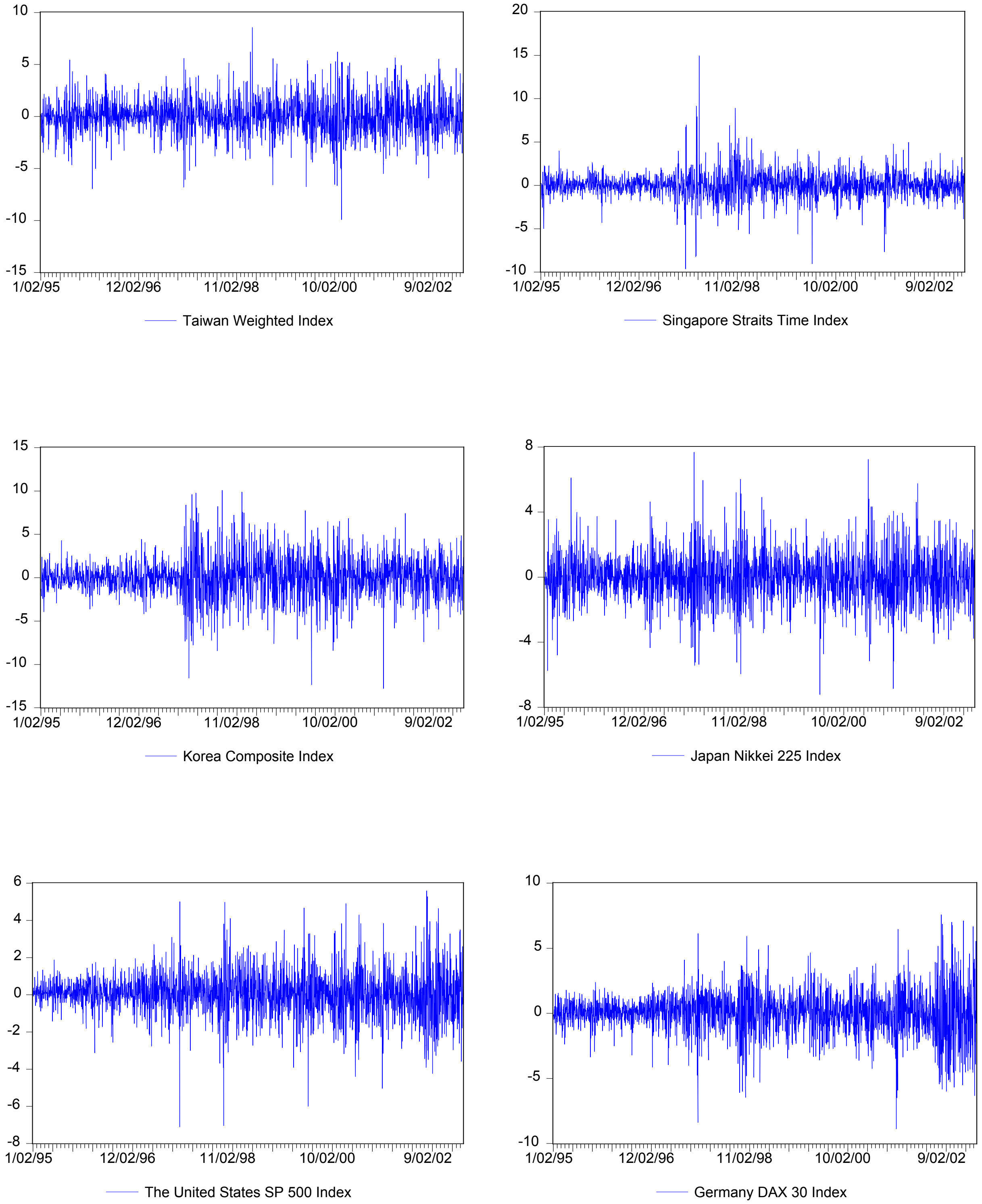


Table 1: Summary descriptive statistics for daily stock price changes

Indices	Sample size	Mean	Std. Dev.	Skewness	Kurtosis
Shanghai A Share Index	2154	0.040	1.953	0.979	29.909
Shenzhen A Share Subindex	2154	0.043	2.030	0.305	18.380
Shanghai B Share Index	2154	0.032	2.324	0.412	7.892
Shenzhen B Share Subindex	2154	0.025	2.503	0.212	9.200
Hang Seng China Enterp Index	2154	-0.034	2.581	0.316	8.932
Hang Seng Index	2154	0.003	1.806	0.151	13.013
Taiwan Weighted Index	2154	-0.021	1.693	-0.012	5.111
Singapore Straits Times index	2154	-0.016	1.479	0.386	13.110
Korea Composite Index	2154	-0.028	2.245	-0.039	5.987
Japan Nikkei 225 Index	2154	-0.041	1.484	0.083	5.082
United States S&P 500 Index	2154	0.030	1.190	-0.106	6.050
Germany DAX 30 Index	2154	0.011	1.647	-0.237	5.796

The starting date is Jan. 2, 1995, and the ending date is Apr. 4, 2003. The starting date and the ending date are for index price, thus the log-price differences have one less observations. The data are daily closing prices, with SHA, SHB, SZA and SZB obtained from SHSE and all the other from Datastream.

Table 2(a): Maximum likelihood estimation of univariate GARCH models for daily stock price changes

	SHA	SZB	HSI	STI	KOSPI	NK225	DAX
Parameter	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
b_0	0.001	-0.037	-0.002	-0.033	-0.046	-0.045	0.039
	(0.031)	(0.041)	(0.029)	(0.024)	(0.037)	(0.029)	(0.026)
b_1	0.013	0.087	0.069	0.121	0.088	-0.038	0.0004
	(0.024)	(0.028)	(0.023)	(0.024)	(0.022)	(0.023)	(0.023)
b_2	-0.014	-0.007	0.018	0.010	0.004	0.002	0.002
	(0.024)	(0.026)	(0.023)	(0.023)	(0.022)	(0.022)	(0.023)
b_3	0.019	0.012	0.058	0.028	-0.014	-0.011	-0.0007
	(0.024)	(0.024)	(0.023)	(0.023)	(0.022)	(0.022)	(0.023)
ω	0.014	0.771	0.041	0.038	0.011	0.051	0.030
	(0.005)	(0.080)	(0.009)	(0.009)	(0.006)	(0.014)	(0.008)
α_1	0.940	0.596	0.916	0.879	0.956	0.920	0.892
	(0.005)	(0.030)	(0.010)	(0.013)	(0.007)	(0.013)	(0.013)
β_1	0.040	0.284	0.013	0.059	0.024	0.017	0.054
	(0.007)	(0.037)	(0.009)	(0.012)	(0.008)	(0.008)	(0.013)
β_2	0.093	0.326	0.133	0.161	0.064	0.100	0.141
	(0.011)	(0.043)	(0.018)	(0.020)	(0.010)	(0.016)	(0.019)
Sample size	2154	2154	2154	2154	2154	2154	2154
Mean log-likelihood	-1.942	-2.166	-1.839	-1.646	-2.099	-1.763	-1.732
Diagnostic test statistics							
$\mathrm{GBP}^1(5)$	-0.211	0.422	-1.130	-0.086	-0.810	-1.142	-1.031
	[0.583]	[0.337]	[0.871]	[0.534]	[0.791]	[0.873]	[0.849]
$\mathrm{GBP}^1(10)$	-0.089	0.518	-1.332	-0.730	-0.878	-1.262	-0.787
	[0.536]	[0.302]	[0.909]	[0.767]	[0.810]	[0.897]	[0.784]
$\mathrm{GBP}^1(20)$	-0.162	0.257	-1.558	-1.168	-0.464	-1.183	-0.402
	[0.564]	[0.399]	[0.940]	[0.879]	[0.679]	[0.882]	[0.656]
$\mathrm{GBP}^2(5)$	-0.064	-0.956	0.293	-0.546	-0.509	-0.169	0.731
	[0.525]	[0.831]	[0.385]	[0.707]	[0.695]	[0.570]	[0.232]
$\mathrm{GBP}^2(10)$	-0.156	-1.330	-0.362	-0.644	-0.891	-0.354	0.187
	[0.562]	[0.908]	[0.642]	[0.740]	[0.814]	[0.638]	[0.426]
$\mathrm{GBP}^2(20)$	-1.073	-1.786	-1.278	-1.096	-0.861	-0.431	0.0004
	[0.858]	[0.963]	[0.899]	[0.864]	[0.805]	[0.667]	[0.500]

The specified model is: $Y_t = b_0 + \sum_{j=1}^{3} b_j Y_{t-j} + \varepsilon_t,\ \varepsilon_t = \xi_t h_t^{1/2},\ h_t = \omega + \alpha_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} > 0) + \beta_2 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} \leq 0)$. The numbers in the parentheses are standard errors for the estimates and the numbers in the square brackets are the $p-$values for the generalized Box-Pierce test test; $\mathrm{GBP}^1(M)$ and $\mathrm{GBP}^2(M)$ are the generalized Box-Pierce test statistics for the first M autocorrelations of the standardized residual and squared standardized residuals, respectively.

Table 2(b): Maximum likelihood estimation of univariate GARCH models for daily stock price changes

	SZA	HKH	TWI	SHB		S&P 500
Parameter	Estimate	Estimate	Estimate	Estimate	Parameter	Estimate
b_0	-0.021	-0.038	-0.029	-0.086	b_0	0.077
	(0.033)	(0.039)	(0.033)	(0.045)		(0.020)
b_1	0.039	0.191	0.032	0.142	b_1	0.022
	(0.025)	(0.024)	(0.023)	(0.026)		(0.023)
b_2	-0.007	-0.026	0.068	0.011	b_2	0.006
	(0.023)	(0.023)	(0.023)	(0.025)		(0.023)
b_3	-0.0001	-0.001	0.018	0.012	b_3	-0.048
	(0.024)	(0.024)	(0.022)	(0.024)		(0.023)
b_4	0.025		-0.047			
	(0.024)		(0.022)			
ω	0.035	0.115	0.120	0.139	ω	0.009
	(0.014)	(0.032)	(0.034)	(0.028)		(0.004)
α_1	0.463	0.349	0.883	0.733	α_1	0.918
	(0.127)	(0.119)	(0.022)	(0.032)		(0.011)
α_2	0.437	0.468				
	(0.119)	(0.111)				
β_1	0.073	0.128	0.019	0.190	β	0.082
	(0.010)	(0.023)	(0.009)	(0.028)		(0.012)
β_2	0.135	0.228	0.136	0.192		
	(0.020)	(0.034)	(0.025)	(0.029)		
d_1				0.107		
				(0.068)		
d_2				0.379		
				(0.082)		
Sample size	2154	2154	2154	2154		2154
Mean log-likelihood	-1.982	-2.165	-1.885	-2.056		-1.481
Diagnostic test statistics						
$\mathrm{GBP}^1(5)$	0.113	-0.309	-1.103	0.667		-1.109
	[0.455]	[0.621]	[0.865]	[0.252]		[0.866]
$\mathrm{GBP}^1(10)$	0.732	-0.869	-0.480	0.570		-0.957
	[0.232]	[0.807]	[0.684]	[0.284]		[0.831]
$\mathrm{GBP}^1(20)$	0.475	-1.230	0.118	0.776		-0.528
	[0.317]	[0.891]	[0.453]	[0.219]		[0.701]
$\mathrm{GBP}^2(5)$	0.507	0.574	-0.427	-0.995		0.020
	[0.306]	[0.283]	[0.665]	[0.840]		[0.492]
$\mathrm{GBP}^2(10)$	0.942	0.054	-0.817	-1.128		-0.431
	[0.173]	[0.478]	[0.793]	[0.870]		[0.667]
$\mathrm{GBP}^2(20)$	-0.070	0.010	-0.560	-1.496		-1.172
	[0.528]	[0.496]	[0.712]	[0.933]		[0.879]

For SHB, the specified model is: $Y_t = b_0 + \sum_{j=1}^{3} b_j Y_{t-j} + d_1 \mathbf{1}(t > 500) + \varepsilon_t,\ \varepsilon_t = \xi_t h_t^{1/2},\ h_t = \omega + \alpha_1 h_{t-1} + d_2 \mathbf{1}(t > 500) + \beta_1 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} > 0) + \beta_2 \varepsilon_{t-1}^2 \mathbf{1}(\varepsilon_{t-1} \leq 0)$.

For S&P500, the specified model is: $Y_t = b_0 + \sum_{j=1}^{3} b_j Y_{t-j} + \varepsilon_t,\ \varepsilon_t = \xi_t h_t^{1/2},\ h_t = \omega + \alpha_1 h_{t-1} + \beta \varepsilon_{t-1}^2$.

Table 3(a): Risk spillover among Chinese stock markets

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔SZA	478.047	340.628	241.758	197.577	171.244	434.681	308.696	218.966	178.839	154.778
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SHA⇐SZA	6.289	4.988	3.499	2.680	2.196	0.720	1.707	1.670	1.420	1.163
	(0.000)	(0.000)	(0.000)	(0.004)	(0.014)	(0.236)	(0.044)	(0.047)	(0.078)	(0.122)
SHA⇒SZA	4.618	5.740	4.750	3.956	3.477	1.381	1.445	1.160	0.686	0.286
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.084)	(0.074)	(0.123)	(0.246)	(0.387)
SHA⇔SHB	60.992	44.750	32.161	26.339	22.623	33.175	25.086	18.319	15.420	13.665
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SHA⇐SHB	2.709	4.043	3.424	2.895	2.223	0.307	2.246	1.901	2.071	2.018
	(0.003)	(0.000)	(0.000)	(0.002)	(0.013)	(0.380)	(0.012)	(0.029)	(0.019)	(0.022)
SHA⇒SHB	0.426	0.424	0.323	0.205	0.144	0.345	0.652	0.893	0.833	0.911
	(0.335)	(0.336)	(0.373)	(0.419)	(0.443)	(0.365)	(0.257)	(0.186)	(0.202)	(0.181)
SHA⇔SZB	57.516	41.690	29.779	24.599	21.380	28.016	19.699	13.970	11.373	9.682
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SHA⇐SZB	4.034	4.391	3.686	3.158	2.838	1.004	0.786	0.722	0.489	0.355
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.158)	(0.216)	(0.235)	(0.313)	(0.361)
SHA⇒SZB	-0.201	-0.396	-0.578	-0.272	-0.272	0.077	-0.278	-0.338	-0.244	-0.399
	(0.579)	(0.654)	(0.718)	(0.607)	(0.607)	(0.469)	(0.609)	(0.632)	(0.596)	(0.655)
SHA⇔HKH	0.288	1.428	2.177	2.921	3.660	-0.206	-0.671	0.292	1.317	1.754
	(0.387)	(0.077)	(0.015)	(0.002)	(0.000)	(0.581)	(0.749)	(0.385)	(0.157)	(0.060)
SHA⇐HKH	0.158	2.052	3.206	3.410	3.754	-0.853	-0.920	0.270	1.060	1.736
	(0.437)	(0.020)	(0.001)	(0.000)	(0.000)	(0.803)	(0.821)	(0.394)	(0.145)	(0.041)
SHA⇒HKH	-0.654	-0.493	-0.433	0.484	1.225	0.123	-0.355	-0.007	0.268	0.395
	(0.744)	(0.689)	(0.668)	(0.314)	(0.110)	(0.451)	(0.639)	(0.503)	(0.394)	(0.346)
SZA⇔SHB	53.013	40.672	29.774	24.320	20.782	41.000	30.459	2.089	18.751	16.497
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SZA⇐SHB	3.661	7.128	6.571	5.512	4.50	2.399	3.054	2.261	2.037	1.615
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.001)	(0.012)	(0.021)	(0.053)
SZA⇒SHB	0.078	0.133	-0.195	-0.391	-0.526	0.163	0.820	1.146	1.724	1.974
	(0.469)	(0.447)	(0.577)	(0.652)	(0.701)	(0.435)	(0.206)	(0.126)	(0.0424)	(0.024)

“⇔” represents the two-way tests for causality in risk between the two stock price changes with respect to I_{t-1}; “⇐” and “⇒” represent one-way causality in risk from the latter to the former and the former to the latter with respect to I_{t-1} respectively; The numbers in the parentheses are the $p-$values.

Table 3(b): Risk spillover among Chinese stock markets

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SZA⇔SZB	48.821	35.723	25.846	21.211	18.412	41.575	29.016	20.055	16.140	13.762
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SZA⇐SZB	2.697	3.769	3.586	3.060	2.737	1.107	0.571	0.450	0.429	0.442
	(0.003)	(0.000)	(0.000)	(0.001)	(0.003)	(0.134)	(0.284)	(0.326)	(0.334)	(0.329)
SZA⇒SZB	0.148	-0.125	-0.289	-0.275	-0.303	-0.324	-0.676	-1.232	-1.424	-1.630
	(0.441)	(0.550)	(0.614)	(0.608)	(0.619)	(0.627)	(0.751)	(0.891)	(0.923)	(0.948)
SZA⇔HKH	1.398	1.870	3.075	3.680	3.809	-0.657	-0.664	0.253	1.137	1.311
	(0.081)	(0.031)	(0.001)	(0.000)	(0.000)	(0.744)	(0.747)	(0.400)	(0.128)	(0.095)
SZA⇐HKH	2.611	3.075	3.756	3.781	3.628	-0.624	-0.695	0.112	0.701	0.847
	(0.005)	(0.001)	(0.000)	(0.000)	(0.000)	(0.734)	(0.757)	(0.455)	(0.242)	(0.198)
SZA⇒HKH	0.214	0.091	0.967	1.722	2.003	-0.290	-0.198	0.345	1.017	1.102
	(0.415)	(0.464)	(0.167)	(0.043)	(0.023)	(0.614)	(0.578)	(0.365)	(0.154)	(0.135)
SHB⇔SZB	141.191	102.542	73.121	59.761	51.987	88.745	64.375	46.008	37.456	32.449
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SHB⇒SZB	3.783	5.179	4.258	3.571	3.370	1.474	3.152	2.533	1.524	1.141
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.070)	(0.001)	(0.006)	(0.064)	(0.127)
SHB⇐SZB	0.976	1.950	1.375	0.970	0.804	1.754	1.362	1.182	1.259	1.226
	(0.165)	(0.026)	(0.085)	(0.166)	(0.211)	(0.040)	(0.087)	(0.119)	(0.104)	(0.110)
SHB⇔HKH	21.590	18.100	13.499	10.950	9.242	11.654	9.182	6.607	5.238	4.436
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SHB⇒HKH	5.747	5.539	3.646	2.371	1.486	3.116	3.341	2.537	1.918	1.726
	(0.000)	(0.000)	(0.000)	(0.009)	(0.069)	(0.001)	(0.000)	(0.006)	(0.028)	(0.042)
SHB⇐HKH	7.137	7.068	5.920	5.223	4.693	-0.644	-0.316	-0.326	-0.370	-0.543
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.740)	(0.624)	(0.628)	(0.644)	(0.706))
SZB⇔HKH	10.339	8.608	6.837	6.556	6.427	8.729	6.780	5.030	4.655	4.326
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SZB⇒HKH	1.261	2.282	2.513	3.035	3.323	0.214	0.712	0.838	0.680	0.577
	(0.104)	(0.011)	(0.006)	(0.001)	(0.000)	(0.415)	(0.238)	(0.201)	(0.248)	(0.282)
SZB⇐HKH	1.019	1.167	0.921	1.139	1.344	0.768	0.845	0.558	1.236	1.492
	(0.154)	(0.122)	(0.178)	(0.127)	(0.089)^a	(0.221)	(0.199)	(0.288)	(0.108)	(0.068)^b

a: the $p-$value is 0.053 for $M = 50$;
b: the $p-$values are 0.0569 and 0.053 for $M = 45, 50$ respectively.

Table 4: Risk spillover among greater China

Panel A: Risk spillover between Chinese stock markets and that of Hongkong

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔HSI	0.432	0.556	1.249	2.125	2.282	0.308	0.108	0.468	1.124	1.442
	(0.357)	(0.411)	(0.265)	(0.132)	(0.079)	(0.379)	(0.457)	(0.320)	(0.131)	(0.075)
SHA⇒HSI	0.432	0.556	1.249	2.125	2.282	-0.139	-0.298	0.581	1.487	1.832
	(0.333)	(0.289)	(0.106)	(0.017)	(0.011)	(0.555)	(0.617)	(0.281)	(0.068)	(0.033)
SHA⇐HSI	0.440	-0.048	-0.218	-0.419	-0.167	-0.519	-0.294	-0.406	-0.271	-0.110
	(0.330)	(0.519)	(0.586)	(0.663)	(0.566)	(0.698)	(0.616)	(0.658)	(0.607)	(0.544)
SZA⇔HSI	0.669	-0.561	0.089	0.657	1.155	1.605	1.122	0.589	1.142	1.389
	(0.748)	(0.713)	(0.464)	(0.256)	(0.124)	(0.054)	(0.131)	(0.278)	(0.127)	(0.082)^{a}
SZA⇒HSI	-0.581	-0.778	0.344	1.332	1.695	1.444	1.063	0.988	1.636	1.746
	(0.719)	(0.782)	(0.365)	(0.091)	(0.045)	(0.074)	(0.144)	(0.161)	(0.051)	(0.040)
SZA⇐HSI	0.078	0.321	0.061	-0.159	0.160	1.153	0.584	-0.173	-0.022	0.222
	(0.469)	(0.374)	(0.476)	(0.563)	(0.436)	(0.125)	(0.280)	(0.568)	(0.509)	(0.412)
SHB⇔HSI	11.083	9.339	6.922	6.052	5.580	10.571	8.513	6.018	5.179	4.721
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SHB⇒HSI	1.465	2.694	2.256	2.467	2.467	1.855	2.795	2.488	2.505	2.294
	(0.071)	(0.004)	(0.012)	(0.007)	(0.007)	(0.032)	(0.003)	(0.006)	(0.006)	(0.011)
SHB⇐HSI	1.096	1.249	0.877	0.634	0.685	-0.316	-0.219	-0.752	-0.727	-0.429
	(0.137)	(0.106)	(0.190)	(0.263)	(0.247)	(0.624)	(0.587)	(0.774)	(0.766)	(0.667)
SZB⇔HSI	7.275	5.685	4.073	3.963	3.790	7.295	5.964	4.166	4.080	4.119
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SZB⇒HSI	0.204	0.348	0.361	0.770	0.735	0.562	0.084	-0.280	-0.200	-0.210
	(0.419)	(0.364)	(0.359)	(0.221)	(0.231)	(0.287)	(0.467)	(0.610)	(0.579)	(0.583)
SZB⇐HSI	2.456	2.186	1.430	1.595	1.812	1.761	2.639	2.046	2.604	3.121
	(0.007)	(0.014)	(0.076)	(0.055)	(0.035)	(0.039)	(0.004)	(0.020)	(0.005)	(0.001)
HKH⇔HSI	108.331	77.605	55.854	46.174	40.198	59.218	41.251	28.826	24.032	21.286
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HKH⇒HSI	5.828	4.150	3.538	2.910	2.397	1.155	0.404	0.407	0.737	1.016
	(0.000)	(0.000)	(0.000)	(0.002)	(0.008)	(0.124)	(0.343)	(0.342)	(0.230)	(0.155)
HKH⇐HSI	-0.330	0.860	1.221	1.690	1.811	-0.669	-1.078	-1.412	-0.862	-0.470
	(0.629)	(0.195)	(0.111)	(0.046)	(0.035)	(0.748)	(0.860)	(0.921)	(0.806)	(0.681)

a: the $p-$value is 0.051 for $M = 50$

Table 5: Risk spillover among greater China

Panel B: Risk spillover between Chinese stock markets and that of Taiwan

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔TWI	-0.262	0.055	-0.541	-0.747	-0.780	-0.231	0.033	-0.502	-1.030	-1.078
	(0.603)	(0.478)	(0.706)	(0.773)	(0.788)	(0.591)	(0.487)	(0.692)	(0.848)	(0.859)
SHA⇒TWI	-0.078	0.639	0.286	0.081	-0.005	-0.343	-0.334	-0.781	-1.062	-1.231
	(0.531)	(0.261)	(0.388)	(0.468)	(0.502)	(0.634)	(0.631)	(0.783)	(0.856)	(0.891)
SHA⇐TWI	-0.137	-0.409	-0.983	-1.086	-1.079	-0.138	0.326	0.004	-0.465	-0.351
	(0.555)	(0.659)	(0.837)	(0.861)	(0.860)	(0.555)	(0.372)	(0.499)	(0.679)	(0.637)
SZA⇔TWI	0.216	0.988	0.481	0.174	0.191	1.713	2.122	1.614	0.962	0.582
	(0.414)	(0.161)	(0.315)	(0.431)	(0.424)	(0.043)	(0.017)	(0.053)	(0.168)	(0.280)
SZA⇒TWI	1.265	2.019	1.308	0.825	0.753	2.014	1.093	0.127	-0.335	-0.622
	(0.103)	(0.022)	(0.095)	(0.205)	(0.226)	(0.022)	(0.137)	(0.449)	(0.631)	(0.733)
SZA⇐TWI	-0.342	-0.145	-0.358	0.377	-0.309	1.164	2.343	2.369	1.830	1.547
	(0.634)	(0.557)	(0.640)	(0.647)	(0.621)	(0.122)	(0.010)	(0.009)	(0.034)	(0.061)
SHB⇔TWI	4.415	3.805	3.283	3.212	2.859	1.525	1.842	1.966	1.752	1.655
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.064)	(0.033)	(0.025)	(0.040)	(0.049)
SHB⇒TWI	-0.198	-0.525	-0.468	-0.149	-0.031	0.029	0.667	0.880	0.855	0.639
	(0.579)	(0.700)	(0.680)	(0.559)	(0.512)	(0.489)	(0.252)	(0.189)	(0.196)	(0.261)
SHB⇐TWI	0.860	1.996	2.333	2.421	2.096	0.436	0.803	1.090	0.945	1.107
	(0.195)	(0.023)	(0.010)	(0.008)	(0.018)	(0.331)	(0.211)	(0.138)	(0.172)	(0.134)
SZB⇔TWI	0.556	0.130	-0.372	-0.267	-0.229	0.223	0.432	0.599	0.622	0.559
	(0.289)	(0.448)	(0.645)	(0.605)	(0.590)	(0.412)	(0.333)	(0.274)	(0.267)	(0.288)
SZB⇒TWI	-0.756	-0.978	-1.040	-1.099	-1.115	0.217	0.411	0.906	1.241	1.155
	(0.775)	(0.836)	(0.851)	(0.864)	(0.868)	(0.414)	(0.340)	(0.182)	(0.107)	(0.124)
SZB⇐TWI	1.991	1.368	0.621	0.815	0.875	-0.104	0.082	-0.140	-0.431	-0.429
	(0.023)	(0.086)	(0.267)	(0.207)	(0.191)	(0.541)	(0.467)	(0.556)	(0.667)	(0.667)
HKH⇔TWI	7.245	6.334	6.107	5.650	5.341	4.102	3.317	2.751	2.073	1.779
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.019)	(0.038)
HKH⇒TWI	2.008	2.561	3.321	3.058	2.904	5.496	4.415	3.557	2.796	2.410
	(0.022)	(0.005)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)	(0.008)
HKH⇐TWI	-0.619	0.185	0.930	1.327	1.511	0.406	0.011	0.040	-0.151	-0.157
	(0.732)	(0.427)	(0.176)	(0.092)	(0.065)	(0.342)	(0.496)	(0.484)	(0.561)	(0.563)

Table 6: Risk spillover between Chinese stock markets and Asian Stock Markets

Panel A: Risk spillover between Chinese stock markets and that of Singapore

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔STI	-0.677	0.058	0.723	1.387	1.710	-1.187	-0.959	-0.608	-0.561	-0.538
	(0.751)	(0.477)	(0.235)	(0.083)	(0.044)	(0.882)	(0.831)	(0.728)	(0.713)	(0.705)
SHA⇒STI	-0.737	-0.115	0.513	1.043	1.382	-0.402	-0.519	-0.336	-0.611	-0.714
	(0.769)	(0.546)	(0.304)	(0.148)	(0.083)	(0.656)	(0.698)	(0.631)	(0.729)	(0.762)
SHA⇐STI	-0.417	0.198	0.546	0.966	1.080	-0.955	-0.535	-0.276	0.025	0.136
	(0.662)	(0.422)	(0.293)	(0.167)	(0.140)	(0.830)	(0.704)	(0.609)	(0.490)	(0.446)
SZA⇔STI	0.268	0.013	0.836	1.295	1.443	-0.967	-0.757	-0.668	-0.741	-0.908
	(0.394)	(0.495)	(0.202)	(0.098)	(0.074)	(0.833)	(0.775)	(0.748)	(0.771)	(0.818)
SZA⇒STI	-0.965	-0.818	0.057	0.394	0.538	-0.245	-0.644	-0.470	-0.285	-0.367
	(0.833)	(0.793)	(0.477)	(0.347)	(0.295)	(0.597)	(0.740)	(0.681)	(0.612)	(0.643)
SZA⇐STI	0.141	0.018	0.615	1.036	1.156	-0.905	-0.205	-0.301	-0.620	-0.796
	(0.444)	(0.493)	(0.269)	(0.150)	(0.124)	(0.817)	(0.581)	(0.618)	(0.732)	(0.787)
SHB⇔STI	9.065	8.100	6.476	5.462	4.678	5.673	4.484	3.417	2.587	2.105
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.018)
SHB⇒STI	1.314	3.890	4.458	4.218	3.681	-0.391	0.340	0.918	0.784	0.619
	(0.094)	(0.000)	(0.000)	(0.000)	(0.000)	(0.652)	(0.367)	(0.179)	(0.216)	(0.268)
SHB⇐STI	-0.592	-0.839	-1.295	-1.422	-1.354	-0.523	-0.205	-0.469	-0.721	-0.763
	(0.723)	(0.799)	(0.902)	(0.922)	(0.912)	(0.700)	(0.581)	(0.680)	(0.764)	(0.777)
SZB⇔STI	9.577	7.385	6.003	5.456	5.018	2.354	1.911	1.560	1.044	0.632
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.028)	(0.055)	(0.148)	(0.264)
SZB⇒STI	-0.450	0.344	1.018	1.747	1.973	-0.504	-0.544	-0.764	-1.198	-1.536
	(0.674)	(0.365)	(0.154)	(0.040)	(0.024)	(0.693)	(0.707)	(0.778)	(0.885)	(0.938)
SZB⇐STI	5.614	3.907	3.007	2.296	1.926	2.309	2.080	2.169	1.949	1.789
	(0.000)	(0.000)	(0.001)	(0.011)	(0.027)	(0.010)	(0.019)	(0.015)	(0.026)	(0.037)
HKH⇔STI	26.728	19.707	14.102	11.272	9.370	24.672	17.678	12.804	10.668	9.316
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HKH⇒STI	1.313	1.719	1.869	1.322	0.946	1.370	0.795	1.081	1.515	1.582
	(0.095)	(0.043)	(0.031)	(0.093)	(0.172)	(0.085)	(0.213)	(0.140)	(0.065)	(0.057)
HKH⇐STI	4.589	3.294	1.758	1.236	0.678	3.305	2.550	1.617	0.956	0.644
	(0.000)	(0.000)	(0.039)	(0.108)	(0.249)	(0.000)	(0.005)	(0.053)	(0.170)	(0.260)

Table 6: Risk spillover between Chinese stock markets and Asian Stock Markets

Panel B: Risk spillover between Chinese stock markets and that of Korea

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔KOSPI	1.286	1.967	1.531	1.544	1.414	0.967	2.361	1.844	1.621	1.836
	(0.099)	(0.025)	(0.063)	(0.061	(0.079)	(0.167)	(0.009)	(0.033)	(0.052)	(0.033)
SHA⇒KOSPI	2.365	2.420	1.138	0.471	0.051	2.235	4.120	3.258	2.335	1.971
	(0.009)	(0.008)	(0.128)	(0.319)	(0.480)	(0.013)	(0.000)	(0.001)	(0.010)	(0.024)
SHA⇐KOSPI	0.271	0.896	1.316	1.932	2.129	-0.809	-0.633	-0.638	-0.056	0.612
	(0.393)	(0.185)	(0.094)	(0.027)	(0.017)	(0.791)	(0.737)	(0.738)	(0.522)	(0.270)
SZA⇔KOSPI	1.104	1.387	1.055	1.059	0.960	0.411	0.466	0.574	0.428	0.309
	(0.135)	(0.083)	(0.146)	(0.145)	(0.169)	(0.411)	(0.466)	(0.574)	(0.428)	(0.309)
SZA⇒KOSPI	0.215	-0.124	-0.619	-0.883	-1.023	0.398	0.589	0.179	-0.093	-0.231
	(0.415)	(0.549)	(0.732)	(0.811)	(0.847)	(0.345)	(0.278)	(0.429)	(0.537)	(0.591)
SZA⇐KOSPI	2.296	2.666	2.451	2.646	2.602	-0.465	-0.744	-0.647	0.198	0.814
	(0.011)	(0.004)	(0.007)	(0.004)	(0.005)	(0.679)	(0.771)	(0.741)	(0.422)	(0.208)
SHB⇔KOSPI	5.729	4.450	3.644	3.568	3.707	7.069	4.835	3.137	2.358	2.120
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.009)	(0.017)
SHB⇒KOSPI	2.033	2.114	1.374	0.681	0.637	1.544	1.140	0.461	0.130	0.253
	(0.021)	(0.017)	(0.085)	(0.248)	(0.262)	(0.061)	(0.127)	(0.322)	(0.448)	(0.400)
SHB⇐KOSPI	-0.623	-0.601	0.380	1.589	2.203	-0.791	-0.911	-0.725	-0.642	-0.584
	(0.733)	(0.726)	(0.352)	(0.056)	(0.014)	(0.785)	(0.819)	(0.766)	(0.740)	(0.720)
SZB⇔KOSPI	2.352	1.337	0.574	0.238	0.329	2.636	1.603	0.904	0.623	0.407
	(0.009)	(0.091)	(0.283)	(0.406)	(0.371)	(0.004)	(0.054)	(0.183)	(0.267)	(0.342)
SZB⇒KOSPI	-0.956	-1.235	-1.310	-1.295	-1.189	-0.815	-1.228	-1.827	-2.071	-2.161
	(0.831)	(0.891)	(0.905)	(0.902)	(0.883)	(0.793)	(0.890)	(0.966)	(0.981)	(0.985)
SZB⇐KOSPI	3.797	2.558	1.660	1.241	1.321	0.952	0.914	1.275	1.458	1.441
	(0.000)	(0.005)	(0.048)	(0.107)	(0.093)	(0.171)	(0.180)	(0.101)	(0.072)	(0.075)
HKH⇔KOSPI	5.331	4.625	4.022	3.984	3.873	17.063	12.998	10.018	8.704	7.814
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HKH⇒KOSPI	-0.803	0.651	1.983	1.942	1.756	1.058	1.793	1.636	1.471	1.299
	(0.789)	(0.258)	(0.024)	(0.026)	(0.040)	(0.145)	(0.036)	(0.051)	(0.071)	(0.097)
HKH⇐KOSPI	2.988	2.062	0.958	1.442	1.762	0.874	0.868	1.373	1.705	1.823
	(0.001)	(0.020)	(0.169)	(0.075)	(0.039)	(0.191)	(0.193)	(0.085)	(0.044)	(0.034)

Table 6: Risk spillover between Chinese stock markets and Asian Stock Markets

Panel C: Risk spillover between Chinese stock markets and that of Japan

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔NK225	-0.333	-0.007	-0.479	-0.881	-0.956	-0.372	0.263	0.523	0.813	0.992
	(0.630)	(0.503)	(0.684)	(0.811)	(0.830)	(0.645)	(0.396)	(0.301)	(0.208)	(0.161)
SHA⇒NK225	-0.449	-0.192	-0.731	-0.938	-1.097	-0.229	0.663	0.884	1.267	1.446
	(0.673)	(0.576)	(0.768)	(0.826)	(0.864)	(0.591)	(0.254)	(0.188)	(0.102)	(0.074)
SHA⇐NK225	0.287	0.439	0.201	-0.199	-0.160	0.098	0.060	0.102	0.088	0.134
	(0.387)	(0.330)	(0.420)	(0.579)	(0.564)	(0.461)	(0.476)	(0.460)	(0.465)	(0.447)
SZA⇔NK225	0.276	0.048	0.484	0.438	0.510	-0.411	-0.518	-0.919	-0.713	-0.448
	(0.391)	(0.481)	(0.314)	(0.331)	(0.305)	(0.659)	(0.698)	(0.821)	(0.762)	(0.673)
SZA⇒NK225	0.890	0.598	0.872	0.852	0.796	-0.848	-0.932	-1.237	-0.735	-0.106
	(0.187)	(0.275)	(0.192)	(0.197)	(0.213)	(0.802)	(0.824)	(0.892)	(0.769)	(0.542)
SZA⇐NK225	-0.485	-0.563	-0.187	-0.238	-0.079	0.002	0.040	-0.180	-0.353	-0.586
	(0.686)	(0.713)	(0.574)	(0.594)	(0.531)	(0.499)	(0.484)	(0.571)	(0.638)	(0.721)
SHB⇔NK225	0.412	0.312	-0.103	-0.006	0.206	4.497	3.262	2.540	1.767	1.263
	(0.340)	(0.378)	(0.541)	(0.502)	(0.419)	(0.000)	(0.000)	(0.006)	(0.039)	(0.103)
SHB⇒NK225	0.153	0.202	-0.431	-0.200	0.004	1.139	1.399	1.010	0.608	0.377
	(0.439)	(0.420)	(0.667)	(0.579)	(0.499)	(0.127)	(0.081)	(0.156)	(0.271)	(0.354)
SHB⇐NK225	-0.756	-0.558	-0.287	-0.265	-0.101	-0.783	-1.046	-0.432	-0.590	-0.749
	(0.775)	(0.712)	(0.613)	(0.605)	(0.540)	(0.783)	(0.852)	(0.667)	(0.722)	(0.773)
SZB⇔NK225	1.676	1.312	1.116	0.878	0.447	8.940	6.858	4.528	3.664	3.098
	(0.047)	(0.095)	(0.132)	(0.190)	(0.328)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
SZB⇒NK225	-0.161	-0.135	-0.255	-0.179	-0.417	0.723	1.348	0.572	0.588	0.421
	(0.564)	(0.554)	(0.600)	(0.571)	(0.662)	(0.235)	(0.089)	(0.284)	(0.278)	(0.337)
SZB⇐NK225	0.171	0.336	0.667	0.461	0.207	-0.871	-0.626	-0.562	-0.632	-0.573
	(0.432)	(0.369)	(0.253)	(0.322)	(0.418)	(0.808)	(0.734)	(0.713)	(0.736)	(0.717)
HKH⇔NK225	8.072	5.757	4.339	3.323	2.589	7.643	5.473	3.846	3.268	2.888
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
HKH⇒NK225	1.151	1.345	1.273	0.895	0.549	0.194	0.375	0.476	0.389	0.390
	(0.125)	(0.089)	(0.102)	(0.186)	(0.291)	(0.423)	(0.354)	(0.317)	(0.348)	(0.348)
HKH⇐NK225	-0.067	-0.577	-0.364	-0.485	-0.618	-0.480	-0.457	-0.573	-0.286	-0.221
	(0.527)	(0.718)	(0.642)	(0.686)	0.732)	(0.684)	(0.676)	(0.717)	(0.613)	(0.587)

Table 7: Risk spillover between Chinese stock markets and major international stock markets

Panel A: Risk spillover between Chinese stock markets and that of the United States

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔S&P500	-0.214	-0.879	-0.969	-1.172	-0.892	-0.835	-0.483	-0.039	0.054	0.032
	(0.585)	(0.810)	(0.867)	(0.834)	(0.880)	(0.879)	(0.858)	(0.798)	(0.515)	(0.487)
SHA⇒S&P500	-1.066	-1.299	-1.365	-1.585	-1.314	-0.159	-0.422	0.469	1.048	1.191
	(0.857)	(0.903)	(0.914)	(0.944)	(0.906)	(0.563)	(0.664)	(0.319)	(0.147)	(0.117)
SHA⇐S&P500	0.096	-0.440	-0.326	-0.329	-0.157	-0.744	0.009	-0.304	-0.791	-0.990
	(0.462)	(0.670)	(0.628)	(0.629)	(0.562)	(0.772)	(0.497)	(0.620)	(0.785)	(0.839)
SZA⇔S&P500	0.373	-0.292	-0.285	-0.180	0.033	-0.395	-0.551	-0.434	-0.359	-0.271
	(0.354)	(0.615)	(0.612)	(0.571)	(0.487)	(0.654)	(0.709)	(0.668)	(0.640)	(0.607)
SZA⇒S&P500	0.108	-0.459	-0.880	-0.907	-0.515	0.371	-0.128	0.206	0.678	0.828
	(0.457)	(0.677)	(0.811)	(0.818)	(0.697)	(0.355)	(0.551)	(0.418)	(0.249)	(0.204)
SZA⇐S&P500	-0.286	-0.509	0.107	0.362	0.317	-0.849	-0.595	-0.762	-1.131	-1.161
	(0.612)	(0.694)	(0.457)	(0.359)	(0.375)	(0.802)	(0.724)	(0.777)	(0.871)	(0.877)
SHB⇔S&P500	1.879	2.253	1.408	0.889	0.728	0.494	0.596	0.239	-0.042	-0.372
	(0.030)	(0.012)	(0.080)	(0.187)	(0.233)	(0.311)	(0.276)	(0.406)	(0.517)	(0.645)
SHB⇒S&P500	1.461	1.264	0.978	0.477	0.279	-0.065	0.680	0.843	0.752	0.537
	(0.072)	(0.103)	(0.164)	(0.317)	(0.390)	(0.526)	(0.248)	(0.200)	(0.226)	(0.296)
SHB⇐S&P500	.371	2.613	1.378	1.044	0.969	1.457	0.592	-0.249	-0.617	-0.904
	(0.009)	(0.004)	(0.084)	(0.148)	(0.166)	(0.073)	(0.277)	(0.598)	(0.731)	(0.817)
SZB⇔S&P500	1.132	0.800	0.261	0.140	-0.214	1.629	1.239	1.021	0.968	0.829
	(0.129)	(0.212)	(0.397)	(0.444)	(0.585)	(0.052)	(0.108)	(0.154)	(0.167)	(0.204)
SZB⇒S&P500	1.206	1.167	0.909	1.043	0.784	0.186	0.179	0.591	1.105	1.143
	(0.114)	(0.122)	(0.182)	(0.149)	(0.217)	(0.426)	(0.429)	(0.277)	(0.135)	(0.127)
SZB⇐S&P500	1.312	0.448	-0.263	-0.627	-0.910	1.683	1.155	0.526	-0.011	-0.215
	(0.095)	(0.327)	(0.604)	(0.735)	(0.819)	(0.046)	(0.124)	(0.300)	(0.505)	(0.585)
HKH⇔S&P500	13.130	11.150	8.308	6.647	5.910	11.347	8.265	5.406	4.601	4.053
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HKH⇒S&P500	5.784	4.964	3.420	2.549	2.060	-0.303	-0.750	-1.144	-1.399	-1.571
	(0.000)	(0.000)	(0.000)	(0.005)	(0.020)	(0.619)	(0.773)	(0.874)	(0.919)	(0.942)
HKH⇐S&P500	14.124	10.671	7.800	6.292	5.767	14.178	10.022	6.781	6.212	5.809
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 7: Risk spillover between Chinese stock markets and major international stock markets

Panel B: Risk spillover between Chinese stock markets and that of German

	$\alpha = 0.10$					$\alpha = 0.05$				
M	5	10	20	30	40	5	10	20	30	40
SHA⇔DAX	-1.033	-1.337	-1.235	-0.968	-0.799	-0.694	-0.805	-0.554	-0.435	-0.378
	(0.849)	(0.909)	(0.892)	(0.833)	(0.788)	(0.756)	(0.789)	(0.710)	(0.668)	(0.647)
SHA⇒DAX	-1.152	-1.150	-0.988	-0.951	-0.908	-1.098	-1.417	-1.014	-0.918	-0.834
	(0.875)	(0.875)	(0.839)	(0.829)	(0.818)	(0.864)	(0.922)	(0.845)	(0.821)	(0.798)
SHA⇐DAX	0.051	-0.488	-0.548	-0.228	-0.050	0.548	0.583	0.470	0.505	0.478
	(0.480)	(0.687)	(0.708)	(0.590)	(0.520)	(0.292)	(0.280)	(0.319)	(0.307)	(0.316)
SZA⇔DAX	0.904	-1.541	-1.306	-1.021	-0.833	-0.518	-0.943	-1.633	-2.025	-2.339
	(0.817)	(0.938)	(0.904)	(0.846)	(0.798)	(0.698)	(0.827)	(0.949)	(0.979)	(0.990)
SZA⇒DAX	-0.734	-1.160	-1.018	-1.066	-1.145	-0.020	-0.468	-1.122	-1.571	-1.825
	(0.768)	(0.877)	(0.846)	(0.857)	(0.874)	(0.508)	(0.680)	(0.869)	(0.942)	(0.966)
SZA⇐DAX	-0.858	-1.244	-0.931	-0.438	-0.074	-0.208	-0.562	-0.997	-1.140	-1.352
	(0.805)	(0.893)	(0.824)	(0.669)	(0.530)	(0.582)	(0.713)	(0.841)	(0.873)	(0.912)
SHB⇔DAX	-0.202	0.287	0.995	0.901	0.878	3.374	2.760	2.011	1.288	1.209
	(0.580)	(0.387)	(0.160)	(0.184)	(0.190)	(0.000)	(0.003)	(0.022)	(0.099)	(0.113)
SHB⇒DAX	-0.731	-0.452	0.150	0.091	0.238	0.705	0.673	0.436	0.036	-0.040
	(0.768)	(0.674)	(0.440)	(0.464)	(0.406)	(0.241)	(0.251)	(0.331)	(0.486)	(0.516)
SHB⇐DAX	0.785	1.146	1.486	1.355	1.147	2.742	2.111	1.537	1.041	1.100
	(0.216)	(0.126)	(0.069)	(0.088)	(0.126)	(0.003)	(0.017)	(0.062)	(0.149)	(0.136)
SZB⇔DAX	5.833	4.227	2.691	2.252	2.179	8.258	7.213	4.894	3.810	3.230
	(0.000)	(0.000)	(0.004)	(0.012)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
SZB⇒DAX	-0.841	-0.873	-0.734	-0.181	0.296	1.906	3.213	2.537	2.163	1.799
	(0.800)	(0.809)	(0.769)	(0.572)	(0.383)	(0.028)	(0.001)	(0.006)	(0.015)	(0.036)
SZB⇐DAX	9.980	6.894	4.378	3.195	2.626	12.638	8.229	4.915	3.571	3.03
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
HKH⇔DAX	12.282	9.273	6.696	5.236	4.345	7.024	6.321	4.515	3.508	2.785
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
HKH⇒DAX	1.586	1.654	1.067	0.636	0.429	4.639	4.866	3.162	2.110	1.420
	(0.056)	(0.049)	(0.143)	(0.262)	(0.334)	(0.000)	(0.000)	(0.001)	(0.017)	(0.078)
HKH⇐DAX	3.617	2.583	2.002	1.497	1.127	3.183	2.230	1.713	1.556	1.369
	(0.000)	(0.005)	(0.023)	(0.067)	(0.130)	(0.001)	(0.013)	(0.043)	(0.060)	(0.086)