Volatility spillovers during the Chinese stock market crisis: a MEM-based approach

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Abstract

We study volatility spillovers from the Chinese A-share market to four Asia-Pacific (APAC) markets and three global markets during the Chinese stock market crisis. We make use of a non-linear model and determine that volatility spillovers tend to be regional, posing greater risks to the region than elsewhere. We show that, during the stock market crash, Chinese stock markets are more integrated in the APAC region. We find no evidence of asymmetric effects and exclude short-run effects of the national team established by the Chinese authorities. We construct a volatility spillover balance and find that, during the financial turbulence, mainland China changes its status from being volatility spillover receiver to volatility generator.

JEL Classification Numbers: C22; C32; C53.

Keywords: Financial contagion, Multiplicative-error model, Volatility spillover balance

The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Council for Social Security Fund, the Bank of Italy or the Eurosystem. All remaining errors are our own.

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1. Introduction

The Chinese economy has grown rapidly in recent decades, as has its integration into the global economy. At the same time, the Chinese stock market has developed at a rapid pace, playing an increasingly important role in financing the continuously booming economy. It has experienced rapid capitalization growth and is now among the most important in the world. Despite being established as recently as 1990, indeed, the Shanghai (SSE) and Shenzhen stock exchanges (SZSE) had grown to become the world's fifth and eighth largest stock markets by capitalization, with $4.0 and $2.5 trillion, respectively, by 2019. International capital flows and larger risk diversification have driven the total market capitalization on the two stock exchanges to be the second in the world just behind the US.

However, as an emerging market, the Chinese stock market is actually still immature and characterized by low accounting standards, weak reporting requirements, and lax regulatory enforcement when compared to developed markets. Stringent capital controls, regulatory curbs, restrictions on the activities of foreign investors, constrained access to credit, the absence of market makers, a large participation of small retail investors, and severe restrictions on short selling are among the features that stand out in this regard.[1]

From late 2014 to the first half of 2015, China experienced a bullish market, with the Shanghai-Hong Kong Stock Connect being a significant channel for foreign capital inflow to Mainland China and possibly contributed to this dramatic market increase in asset price bubbles. Immediately after, the Chinese A-share market experienced three major market crashes between mid-June 2015 and early January 2016. The first occurred from mid-June to early July of 2015. The China Securities Regulatory Commission (CRSC) banned all securities companies from shadow margin lending.[2] Such shift forced many arbitrage positions to be closed out at a loss, causing the market to fall even further. Leverage-induced fire sales and heavy selling by margin investors fueled the crash. The Shanghai and Shenzhen Stock Exchange Composite Indexes fell by 32% and 39%, respectively, wiping out more than RMB 26 trillion in share value from their peaks on June 12. Following a brief period of stability, another collapse occurred in mid-August 2015, when the Chinese government unexpectedly devaluated the RMB by about 2%. Until late August 2015, the stock index fell by nearly 26%, wiping out more than RMB 16.5 trillion in share value. Following the second collapse, the market gradually recovered. However, the stock market experienced another drop on January 4, 2016, when the Shanghai and Shenzhen exchanges implemented the Circuit Breaker rule.[3] As soon as the Circuit Breaker rule was

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[1] The Chinese stock market is characterized by retail trading, with investors accounting for approximately 20% of capitalization but 80% of trading volume. Short selling was banned before 2010, and only allowed for selected stocks after that. Furthermore, a stock cannot be bought or sold if it is suspended from trading, or if the stock hits its daily upper or lower price limit, equal to 110 or 90% of its previous day's closing price, respectively.

[2] The brokerage-financed margin system, which allows retail investors to obtain credit from their brokerage firms is tightly regulated by CRSC. Investors must be sufficiently wealthy and experienced to qualify for brokerage financing; and the CRSC imposes a market-wide maximum level of leverage—the Pingcang Line—beyond which the account is taken over by the lending broker, triggering forced liquidation. In contrast, the shadow-financed margin system falls in a regulatory grey area. Shadow-financing is largely unregulated by the CRSC; there is no maximum Pingcang Line and lenders generally do not impose restrictions on borrower wealth, trading experience, or financial literacy

[3] Such temporary measure was devised in such a way that if the Shanghai and Shenzhen 300 Index rises or falls by more than 5%, the stock market will be halted for 15 minutes (Level I). Furthermore, if the increase or

implemented, the stock market dropped 7%, triggering Level I and then Level II after only 6 minutes of the market reopening.

During the crisis, the Chinese government implemented a number of rescue policies—lowering interest rates, banning IPOs, investigating rule-breaking, cracking down market rumours, and restricting share sales by large shareholders—and also established a national team to directly purchase stocks traded on the exchanges. Chinese state-backed funds—China Securities Finance Corporation Limited (CSF) and China Central Huijin Investment Limited (CCH)—intervened directly on the stock market by purchasing shares and indirectly by providing funding to 21 brokerages.[4]

The current study is motivated by the Chinese stock market's growing importance on a global scale. Even if the Chinese stock market crisis is liquidity-driven and caused by a decline in the number of market participants or difficulties in trading financial assets rather than changes in the economic environment, corporate debt, or operational problems, it is expected to have a significant impact, particularly in the APAC region, given China's global economic influence. Furthermore, because of their overall exposure to China's export risk, the crash caused by the unexpected devaluation of the RMB and the resulting panic in the Chinese financial market might been transmitted to other trading partners.

It is widely acknowledged that features of China's financial system helped insulate the country crisis from the Asian currency. If, at that time, the country was immune to external shocks due to its unique characteristics—capital controls, regulatory curbs, absence of market makers and retail investors—we are interested in investigating interdependences and volatility transmission mechanisms when such a setup faces a domestic shock. Even if the Chinese stock market is not fully integrated and completely accessible, we want to investigate the regional and global consequences of the stock market crisis.

Several studies provide constructive theoretical and empirical discussion on the financial linkages among stock markets. Goldstein (1998) discusses the 'wake-up call' hypothesis to explain how shocks in one country may push investors to take a closer look at fundamentals of similar countries. Pretorius (2002) defines and studies three possible market co-movements, specifically, contagion effect, economic integration and stock market characteristics. Theodossiou and Lee (1993) documents uni-directional return and volatility spillovers from relatively mature markets to emerging countries. Bae and Karolyi (1994) and Koutmos and Booth (1995) focus on the asymmetric impacts of good and bad news, discovering an asymmetric volatility transmission mechanism, i.e., volatility spillovers manifest more when the news is bad.[5]

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decrease exceeds 7%, stock market trading will be suspended for the day (Level II). On January 8, 2016, the Circuit Breaker rule was abandoned.

[4] These brokerages include affiliates of the State Administration of Foreign Exchange, CSF customized asset management plans, and CSF customized funds. Rather than rescuing companies from routine operational problems, the national team was motivated solely by the desire to quickly stabilize the stock market. Since July 6, 2015, the national team has directly purchased over 1000 stocks. Such information was made available to investors through company announcements, information shared by company insiders, or quarterly earnings reports that included the disclosure of the top-10 shareholders obtained directly from the secondary market.

[5] As pointed out by Rigobon (2019) "the distinction between contagion and spillover is tenuous...The definition of what constitute spillover and what is contagion is model dependent...In other words, if the strength in the co-movement is of the order of magnitude of the researcher's believe, then it is called spillover, but if the co-movement is higher, then it is interpreted as contagion".

The impacts of such shocks are also relevant in order to assess to which extent globalisation and regional integration lead to increasing equity market interdependence. Existing literature has widely studied and established the leading role of the US market in generating global spillovers. (Eun and Shim (1989), Lin et al. (1994), Kim et al. (2016), Ng (2000), Yang et al. (2003)). At the same time, regional financial centres have great significance in studying the dynamics of shocks and financial spillovers. Kim and Rogers (1995) and Masih and Masih (1999) study the role of regional financial centres (Japan or Hong Kong) and show that Asian stock market fluctuations are significantly guided by their regional markets rather than by the US market. When studying the Asian currency crisis, Engle et al. (2012) find that shocks originating in Honk Kong are amplified in their transmission throughout a network of interdependencies.

Interdependencies between the Chinese stock market and other emerging markets have received less attention, with mixed results. Cheng and Glascock (2005) find no cointegration between the Greater China Economic Area (GCEA) stock markets, including Mainland China, Hong Kong, and Taiwan, and two developed markets, Japan and the US. Wang and Firth (2004) provide evidence that information from at least one of the three developed markets' daytime returns (Tokyo, London and New York) predicts overnight returns on all GCEA stock markets due to contemporaneous unidirectional spillovers. The long-run equilibrium relationship, spillovers and information transmission mechanisms among the GCEA stock markets have been investigated by Bahng and Shin (2004), Johansson and Ljungwall (2009) and Huang and Kuo (2015). Fan et al. (2009) study the dynamic linkage between the Chinese and overseas stock markets, providing evidence of a long-term comovement. Lean and Teng (2013) and Giovannetti and Velucchi (2013) observe financial integration among mainland China, Malaysia and African financial markets, respectively. Wang (2014) analyzes the impacts of the global financial crisis among East Asia stock markets and document that afterwards the interdependence between the Chinese stock market and East Asian markets has increased. Nishimura et al. (2015) report that the Chinese stock market influences the Japanese stock market via China-related firms in Japan.

In this paper, we contribute to the literature that examines spillovers effects of the Chinese stock market crash by directly modelling volatility spillovers. It is important to highlight how our study differs from previous research of the Chinese stock market crisis. Ahmed and Huo (2019) study spillovers between China and major stock markets during the stock market crisis and find significance of price and volatility spillovers, suggesting that China is becoming more integrated with the regional financial markets. They apply a dynamic GARCH model to investigate spillover effects for 12 groups of pairwise stock markets, which include China and one of the APAC markets, providing evidence of the regional market integration. The novelty value of our research lies in the measure we select to measure volatility spillovers. Rather than the conditional variances of returns like in the GARCH model, we measure volatility by the highest and lowest price recorded during a trading day. While daily returns are based on the previous trading day's closing price, the high-low spread is based on what is observed during the day, taking all trade information into account.[6]

We identify three different stages (before, during and after the crash) and build a volatility proxy based on our daily range. In order to test the effect of both regional and global spillovers, Hong Kong, Singapore, Japan and Australia are included for regional study, while United States, United

[6] A zero return, indeed, is not necessarily informative about what happened during the day, and by the same token, a high return may signal either high volatility during the day or just an opening price much different from the closing price the previous day but very close to the closing price of the same trading day, with a small high-low spread.

Kingdom and Nigeria are used for the research of the global effect.[7] Subsequently, we apply a multiplicative-error model (MEM) to the daily range data. The MEM-based approach defines volatility as function of each own's past and the past of other market's volatilities, directly models expected values of volatility and generates momentum in time-dependent volatility dynamics through multi-period forecast and impulse response functions.[8,9]

Furthermore, we add to the existing literature on the Chinese stock market crisis by examining the role of Chinese government intervention into the stock market. The direct purchase of shares in many listed companies by the national team is different from government bailout programs in other countries during times of crisis. Huang et al. (2019) show that the government intervention increases the value of the rescued non-financial firms. Cheng et al. (2022) find that the national team's interventions reduce the stock price crash risk, increase stock price synchronicity, transaction cost and decrease idiosyncratic information for the firms purchased by the national team. We rather focus on the Chinese stock market as a whole by looking at the stock market index itself. Our MEM-approach incorporate asymmetric effects in which the impact from its own lagged volatility is split into two terms according to whether the lagged market returns are positive or negative, respectively. Finally, we measure the volatility spillover balance as the ratio of the average responses "from" to the average response "to" (excluding one's own), to evaluate total volatility created by the Chinese market relative to the volatility received by other markets.

We discover that, despite the rising importance of Chinese stock market and the cross-industry interdependences among markets, even when modelling directly at volatility spillovers and including international markets not belonging to the APAC region, the effects of the Chinese stock market crisis are regional and not global, in line with Ahmed and Huo (2019). We report significant volatility spillovers added during the crisis in Hong Kong, Japan and Singapore, suggesting that shocks originating during the Chinese financial turbulence may be amplified in their transmission throughout the system, posing greater risks to the region than elsewhere. At the same time, we observe that parameters shifted during and after crisis, making the system more unstable. If, before the crisis, the Chinese stock markets seemed to be independent of other equity markets, with no evidence of volatility spillover from other markets, the same market has now changed its own nature and become more integrated in the APAC region. Our MEM-based approach provides no evidence that the Chinese stock market has benefited from the stabilising measures implemented by national team: We find no evidence of extra asymmetry added during the financial crisis.

During the financial turbulence the Chinese markets shift its status from being volatility receiver to volatility generator. Before the crash, the volatility spillover balance is indeed below the threshold of one, signaling that the Chinese stock markets absorb volatility. During the crisis, instead, the spillover balance is much higher than one, suggesting that China exports volatility. At the regional

[7] We select Australia, Hong Kong, Japan and Singapore to investigate regional effects, i.e., how shocks propagate over the Asia-Pacific (APAC) region. Global shocks must be identified by the United States and the United Kingdom, given their leading role. Giovannetti and Velucchi (2013) show how Chinese financial market volatility depends on African markets (Egypt, Ghana, Kenya and South Africa) but Nigeria. Moreover, the Nigerian market is relatively independent of other African markets. Among all African markets, we select Nigeria to see if, in the last decade, the volatility transmission mechanism has changed.

[8] According to Engle et al. (2012), the main advantage of the MEM with respect to a multivariate GARCH stands in the possibility of analyzing more interdependencies at once, without suffering from limitations in the number of variables to be considered.

[9] Martin and Dungey (2007) provides an impulse response function in a GARCH contest, but the advantage of a MEM stands in its ability to capture momentum.

level, China and Hong Kong swap their status, with Hong Kong absorbing volatility from mainland China. In the post-crash period, both mainland China and Hong Kong return to the group of countries that receive and generate volatility spillovers, respectively. Despite shocks have been originated in China, vice versa, both United States and Japan remain in the same class for the entire period: they export volatility before, during and after the financial crisis.

The remainder of the paper is structured in the following way. Section 2 describes the data and the variable we use as volatility proxy. Section 3 introduces the vector MEM, providing a summary of the estimation results and residual diagnostics. Section 4 discusses volatility forecasts, impulse response functions and volatility spillover balance. Concluding remarks follow in Section 5.

2. Volatility proxy

We focus attention on daily volatility in five APAC markets and three non-APAC markets: China (CHN), Hong Kong (HK), Japan (JP), Singapore (SI), Australia (AUS), Nigeria (NIG), United Kingdom (UK) and United States (US). Data are provided by the WIND database. We select the SSE to represent the Chinese market.[10]

We identify the "crisis period" as the period from June, 12, 2015 to January, 28, 2016. We use the highest and lowest price recorded during the day to build our volatility proxy, the daily range hl_t:[11]

$$hl_t = \sqrt{\frac{\pi}{8}}(\log(high_t) - \log(low_t)). \tag{1}$$

Figure 1 describes the behaviour of the stock indices. Even if various markets show different trends within the period from January 2010 to March 2017, most of them fall during the Chinese stock market crisis as shown by the shaded area. During the crisis, the Shanghai Composite Index reaches both its highest and lowest value for a long time series. All other markets experience a downward trend during the crisis period.

[INSERT FIGURE 1 HERE]

Figure 2 shifts attention to our volatility measure, hl_t, for all markets. Markets experiencing a huge decline during the crash have a sharp increase in the daily range. Spikes in hl_t are noticeable in the APAC markets, while others, like the United States, fluctuate less.[12]

[INSERT FIGURE 2 HERE]

[10] As said above, individual investors dominate stock trading both in SSE and SZSE. One of the key differences between the two stock exchanges stands in the type of listed companies: state-owned enterprises (SOE) are usually listed in Shanghai, while the SZSE is more oriented towards private companies.

[11] The volatility proxy hl_t can be interpreted as the maximum intraday return obtainable on a long position entered at the lowest price and closed at the highest, (if the former precedes the latter) or on a short position if the highest price was recorded before the lowest. See Parkinson (1980) and Engle, Gallo, and Velucchi (2012) for a detailed discussion on the properties of hl_t.

[12] However, it is worth noting how volatility jumps due to unexpected events, like Brexiteers winning in the referendum or Donald J. Trump being elected president of the United States.

Table 1 summarizes the descriptive statistics for all the financial markets in our sample. We break up the mean of the range by sub-periods (pre-crisis, crisis, and post-crisis) to identify the volatility dynamics in a more comprehensive manner.[13]

During the crash, volatility grows dramatically for the Chinese stock market. The mean value is 1.689. Volatility increases also for the other markets. However, volatility does not exhibit a permanent increase since the daily range in the post-crisis period is much lower with respect to the stock market crash. The declining trend is not homogenous because Japan and Singapore have post-crisis means higher than their pre-crisis counterparts, while the rest have lower values. The post-crisis average is marginally higher than its pre-crisis value for the Australian market, too. This might identify the effects of the aftermath of the crisis, but also suggest a decreasing/increasing trading intensity within each market and across markets.[14]

[INSERT TABLE 1 HERE]

3. Volatility spillovers

Daily range in Equation 1 defines a non-negative process. We assume that its dynamics is described by a multiplicative error model (MEM) proposed. Conditional on the information set I_{t-1}, the volatility in market i can be modelled as:

$$hl_{i,t}|I_{t-1} = \mu_{i,t}\varepsilon_{i,t}, \qquad i = 1, \dots, 8 \tag{2}$$

Where the innovation term $\varepsilon_{i,t}$ is a gamma random variable with unit conditional expectation, i.e., $\varepsilon \sim \Gamma(\alpha, \beta)$ with a single parameter $\phi \coloneqq \alpha\beta$.

We derive the base model to study the single market i by computing the expected value of Equation 2:

$$\mu_{i,t} = \omega_i + \beta_i \mu_{i,t-1} + \alpha_{i,i} hl_{i,t-1}. \tag{3}$$

Equation 3 defines a MEM(1,1) involving past value range and of the conditional expectation.

The base model defined in Equation 3 is our starting point; we enrich the specification in order to include:

- A second lag on past range $hl_{i,t-2}$ when the residual performance fails to reject the hypothesis of zero-correlated residuals.
- Two dummy variables, $D_{i,t}^{-}$ and $D_{i,t}^{+}$ to capture asymmetric effects, that is, whether lagged market returns are negative.

[13] Parkinson (1980) assumes zero mean excess. Maximum likelihood (ML) estimates support his assumptions, since our stock market indexes have mean quite close to 0.

[14] It is worth noting that the Japanese index tumbled into bear market territory since mid-2015 due to concern about strengthening of the yen, seen as a safe haven in an insecure regional economic context. If the yen keeps appreciating, it could hurt companies' international competitiveness and cut into the export sector's profits.

- Interaction among different markets, through the lagged daily ranges observed in other markets $hl_{j,t-1}$, $j \neq i$.

- Time dummies: DC_t (during crisis = 1 between May, 12, 2015, and January, 28, 2016) and PC_t (post-crisis = 1 from January, 29, 2016 onwards).

- Interaction terms between daily ranges of all markets and DC_{t-1} to accommodate the possibility of changing links during the crisis.

- An interaction between DC_{t-1} and the asymmetric effects.

We also incorporate asymmetry to capture upside and downsize effects, so that the enriched model becomes:[15]

$$
\begin{aligned}
\mu_{i,t} = \omega_i + \beta_i \mu_{i,t-1} + \alpha_{i,i}^{-} hl_{i,t-1} D_{i,t}^{-} + \alpha_{i,i}^{+} hl_{i,t-1} D_{i,t}^{+} \\
+ \sum\nolimits_{i \neq j} \alpha_{i,j} hl_{j,t-1} + \gamma_{i,i}^{-} hl_{i,t-1} DC_{t-1} D_{i,t}^{-} \\
+ \gamma_{i,i}^{+} hl_{i,t-1} DC_{t-1} D_{i,t}^{+} + \sum\nolimits_{i \neq j} \gamma_{i,j} hl_{j,t-1} DC_{t-1} \\
+ \delta_i DC_{t-1} + \lambda_i PC_{t-1} + \Psi hl_{i,t-2}.
\end{aligned} \tag{4}
$$

Equation 5 describes the initial model to start with:

$$
\mu_{i,t} = \omega_i + \beta_i \mu_{i,t-1} + \alpha_{i,i}^{-} hl_{i,t-1} D_{i,t}^{-} + \alpha_{i,i}^{+} hl_{i,t-1} D_{i,t}^{+} \tag{5}
$$

Based on the equation-by-equation estimation results, we build our selected model upon the base model. We test if $\alpha^{-} = \alpha^{+}$ in order to decide whether to keep the asymmetric terms or replace them with pure lag 1 term. We perform additional diagnostic test on residuals to check if the model suffers from auto-correlation, which determines if we should include additional lagged term. Then, we expand the model to the most general form, including spillover terms, spillover terms during crisis, interaction variables. In order to capture the effects of the measures implemented by the Chinese national team, we introduce and test asymmetric terms during the crisis, i.e., $\gamma^{-} = \gamma^{+}$.

Table 2 report the selected specification for each market, with a cross X indicating the presence of significant additional links relative to the own market (base) specification. Diagnostic analysis suggests a MEM(2,1) for Japan and Nigeria, while the dynamics of the other markets are described by a MEM(1,1). All markets outline significant interactions with one another, even during the financial turbulence. The way relationships change depends on the specific market. Mainland China shows complex dynamics due to shifts in the constant term of the model during and after the crisis, in line with the view that the country encounters particular turmoil during the crisis. Singapore, United Kingdom and United States experience shifts in the constant term of the model after the crisis. Parameters shift for United Kingdom and the United States might be caused by the political uncertainty induced by Brexit and the 2016 United States presidential election. Hong Kong, Japan, United Kingdom and United States, reveal significant reaction of volatility to news in their own markets. Vice versa, China does not exhibit any significant reaction of volatility to news, providing

[15] As in Engle et al. (2012), we conduct a model selection process to simplify the most general form without losing any explanatory power. Model selection starts with the base model, in which the conditional expectation of realised volatility is modelled on past realised volatility and the conditional expected volatility of the market itself.

evidence that, despite the efforts of the government and Chinese Security regulatory committee, either institutional or individual investors do not react immediately.

[INSERT TABLE 2 HERE]

Table 3 supports the model selection process. For both base and selected model we report the values of the log-likelihood functions, and the Ljung-Box test statistics for the null of no autocorrelation in the residuals and squared residuals. The estimated gamma parameter φ_i for the distribution of standardised residuals is:

$$\hat{\phi}_i^{\,-1} = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{hl_{i,t}}{\hat{\mu}_{i,t}} - 1\right)^2. \qquad (6)$$

We demonstrate the inadequacy of the base specification, showing that no market can be seen as independent of other markets. Except Nigeria, there is no big gap between the estimated parameters, most of which are around 3 to 6, indicating similar volatility processes within the system. Empirical results in Table 3 suggest evidence that the impact of the Chinese stock market crisis is local rather than global, since the five APAC markets receive significant of added spillovers. Before the crisis, the Chinese seems to be quite unconnected with other markets, since there is no evidence of volatility spillover from other markets. As the stock market, instead, the same market changes its nature and receive volatility spillovers from other markets. Even the Japanese market, that plays a leading role in the regional context, suffers from volatility spillovers added during the crisis period. When looking at global effects, only Nigeria seems to be affected by the Chinese financial turbulence, while the other two markets, chosen to identify global spillovers, have no significant spillover coefficients. In particular, the financial crisis seems not to affect the US and its global leading role: We do not find no evidence of volatility spillover to the US market from other markets.

[INSERT TABLE 3 HERE]

Detailed coefficient estimates and corresponding p-values of both base and selected model for the eight markets are provided in Table 4 and Table 5, where some interesting dynamics in the transmission of shocks are pointed out. First of all, each financial market depends on its own performance and reacts to its past volatility.[16] When looking at the cross-average effects of financial markets, we can note that the Chinese market is not affected by any market but Nigeria. However, during the stock market crash, shocks are transmitted from Australia and Hong Kong to China, with different signs: Australian shocks mitigate the volatility of the Chinese stock market, while shocks from Hong Kong magnify. On other side, the US market seems to react only to Japan and Singapore, with no volatility added during the crisis.

When looking at the APAC region, we find that Australia reacts to shocks from the US and the UK markets, but, during the crisis, shocks originating in Hong Kong mitigate the volatility in the market, while shocks in the UK amplify. Hong Kong reacts to shocks originating in the Chinese, Japanese, Singaporean and American market. During the crisis, shocks originating in Hong Kong mitigate the volatility of the Australian market. The Japanese market, instead, reacts to shock originating in Hong Kong. However, during the crash, shocks originating in Australia mitigate the volatility of the market,

[16] Note that Japan and Nigeria are the only markets in the base model where asymmetric are not significant.

while shocks originating in Singapore and the United States magnify the effect. On the other side, Singapore reacts only to shocks originating in the United States. When the Chinese stock market crashes, shocks from the United Kingdom amplify the volatility, while Japanese shocks mitigate.

Then, we shift our focus to the other two global markets, Nigeria and United Kingdom. We find that Nigeria reacts only to shocks originating in Australia, Japan and Singapore. During the stock market crash, shocks originating in Australia and United Kingdom are transmitted to the Nigerian market. When the Chinese stock market crashes, shocks in the British market mitigate the volatility.[17] The United Kingdom reacts, instead, to shocks originating in the United States. However, during the crisis, shocks in Japan mitigate the volatility while shocks in the United States magnify.

When most markets are in a downward trend, market volatility is significantly higher. Therefore, we examine the national team's efforts to stabilize the market and determine whether any additional asymmetry was introduced during the crisis. Empirical results show that no additional asymmetry is added or narrowed, showing that the national team's stimulus has been ineffective in reversing the asymmetric pattern of increased volatility during bad times. We believe that the actions taken by the national team lead both individual and institutional investor to bet on "what is next'", causing a more volatile market due to different expectations. Our beliefs are based on the dynamics of block trading and leverage.[18] We compute the B/V variable, measured as the ratio between the volume of block trading and the total trading volume, as a parsimonious measurement of information asymmetry.

Figure 3 compares the B/V ratio, lower figure, and total trading volume, upper figure, from 2013 to 2017, and shows that, while total trading volume during the crash is on average larger than before and after the crisis, the B/V is relatively low.

[INSERT FIGURE 3 HERE]

At the same time, leverage plays a key role, not only exaggerating volatility but increasing the market sensitivity. We measure leverage as margin balance over free-float market cap. Figure 4 depicts the leverage dynamics, quite similar to the market index. During the crash, there is a significant decrease in the leverage investors are able or willing to take, that, reasonably, partly reflects market confidence. The relationship between leverage levels and selling is especially strong on days when stock market prices falls, consistent with a downward spiral in which investors forced to deleverage contribute to asset price declines, thereby tightening leverage constraints and forcing more investors to sell assets.[19]

[INSERT FIGURE 4 HERE]

[17] Note that, besides China, Nigeria seems to be the only market not reacting to shock in the United States, not even during the stock market crash.

[18] Pan and Zhu (2015) show that in the Chinese stock market, dominated by individual investors, block trading contributes to the firm-specific information measured by the stock return synchronicity.

[19] See Bian et al. (2018) for more details.

4. Volatility forecasts and response to shock

The next step is to provide the dynamic nature of volatility spillovers. Based on the information available at time t, the conditional expectation of hl_{t+1} for each market can be written compactly as:[20]

$$\boldsymbol{\mu_{t+1}} = \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + \boldsymbol{B\mu_t} + \boldsymbol{A}^*\boldsymbol{hl_t} + \Gamma \boldsymbol{hl_t} DC_t + \boldsymbol{A_2 hl_{t-1}}. \qquad (7)$$

Moving steps forward, $\boldsymbol{hl_{t+\tau}}$, $\tau > 0$ is unknown and needs to be expected with its conditional expectation $\boldsymbol{\mu_{t+\tau}}$. The dummies DC and PC are fixed to the value that they had in t.
Hence, for $\tau = 2$:

$$\begin{aligned}\boldsymbol{\mu_{t+2}} &= \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + \boldsymbol{B\mu_{t+1}} + \boldsymbol{A}^*\boldsymbol{\mu_{t+1}} + \Gamma\boldsymbol{\mu_{t+1}} DC_t + \boldsymbol{A_2 hl_t} \\ &= \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + (\boldsymbol{B} + \boldsymbol{A} + \Gamma DC_t)\boldsymbol{\mu_{t+1}} + \boldsymbol{A_2 hl_t},\end{aligned}$$

and, recursively, for $\tau > 2$

$$\begin{aligned}\boldsymbol{\mu_{t+\tau}} &= \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + (\boldsymbol{B} + \boldsymbol{A} + \Gamma DC_t)\,\boldsymbol{\mu_{t+\tau-1}} + \boldsymbol{A_2 \mu_{t+\tau-2}} \\ &= \boldsymbol{\omega} + \boldsymbol{A_1 \mu_{t+\tau-1}} + \boldsymbol{A_2 \mu_{t+\tau-2}}. \qquad (8)\end{aligned}$$

We use Equation 7 and Equation 8 to look into how the volatilities evolved from late May of 2015, right before the stock market crash, to the period of 90 days ahead. We focus on the four markets we believe more interesting: China, Hong Kong, Singapore and United Kingdom.[21]

Volatility forecasts are shown in Figure 5. Starting from late May, 2015, the evolution of the initial forecasts shows that the Chinese stock market mainly react to its own innovations. By looking along vertical sessions, we see an increase in the progressive volatility forecasts that continues until the third week of July. Hong Kong reacts quickly with an initial upward jump in most volatility forecast lines, that exceeds the long-run volatility. There are few cases where the jump does not occur initially, but immediately after. The effect then slowly turns down. Singapore exhibits a hump-shaped profiles evidence of a later date at which the volatility is projected to peak, that overshoots the long-run volatility due to the accumulation of the combined interactions across market. The United Kingdom exhibits a hump-shape pattern that different from Singapore does not exceed the long-run volatility, that might increase due to the political uncertainty induced by Brexit. The different behaviour might be due to geographical proximity, trade channels, market features or specific events, like the Hong Kong-Shanghai connect, that creates a bridge between the two stock markets.

[INSERT FIGURE 5 HERE]

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[20] When taking into account asymmetric effects, both $\alpha_{i,i}$ and $\gamma_{i,i}$should be replaced with $\alpha_{i,i}^{+}, \alpha_{i,i}^{-}, \gamma_{i,i}^{+}, \gamma_{i,i}^{-}$, accordingly.

[21] As said before, Japan experiences its own stock market crash during that period, so it is reasonable to believe that volatility forecasts might not behave in the same way as we expect. United Stated and Australia are quite similar to the United Kingdom, while Nigeria is exposed to many other uncontrolled spillover factors. Additional results and figures are available from the authors on request.

We also focus on how each market responds to mainland China shocks. The MEM system can be written in a matrix form:

$$\boldsymbol{hl_t} = \boldsymbol{\mu_t} \odot \boldsymbol{\varepsilon_t}, \tag{9}$$

With $\boldsymbol{hl_t}$ being a vector with stacked $hl_{i,t}$'s, $\boldsymbol{\mu_t}$ a vector with stacked $\mu_{i,t}$'s, $\boldsymbol{\varepsilon_t}$ a jointly multivariate independently identically distributed vector with an expected value equal to $\mathbf{1}$ and variance-covariance matrix denoted as $\boldsymbol{\Sigma}$, and $\odot$ representing the element-by-element multiplication. The conditional expectation of $\boldsymbol{hl_{t+\tau}}$ can be seen as the expected value of $\boldsymbol{hl_{t+\tau}}$ given $\boldsymbol{\varepsilon_t}$ being equal to the unit vector $\mathbf{1}$:

$$\boldsymbol{\mu}_{\boldsymbol{t}+\tau} = \boldsymbol{E}\left(\boldsymbol{hl}_{\boldsymbol{t}+\tau} | \boldsymbol{I}_{\boldsymbol{t},} \boldsymbol{\varepsilon_t} = \mathbf{1}\right). \tag{10}$$

By defining a generic vector of shocks $\boldsymbol{s}^{(i)}$, we can derive a different dynamic solution:

$$\boldsymbol{\mu}_{\boldsymbol{t}+\tau}^{(\boldsymbol{i})} = \boldsymbol{E}\left(\boldsymbol{hl}_{\boldsymbol{t}+\tau} | \boldsymbol{I}_{\boldsymbol{t},} \boldsymbol{\varepsilon_t} = \mathbf{1} + \boldsymbol{s}^{(i)}\right). \tag{11}$$

By posing the ith element equal to the unconditional standard deviation of ε_{it} and the other terms $j \neq i$ equal to the linear projection:

$$E\left(\varepsilon_{j,t} | \varepsilon_{i,t} = 1 + \sigma_i\right) = 1 + \sigma_i \frac{\sigma_{i,j}}{\sigma_i^2}. \tag{12}$$

Similarly, we can also derive the relative change in expected volatilities in vector form:

$$\rho_{t,\tau}^{(i)} = \left(\boldsymbol{\mu}_{\boldsymbol{t}+\tau}^{(\boldsymbol{i})} \oslash \boldsymbol{\mu}_{\boldsymbol{t}+\boldsymbol{\tau}}\right) - \mathbf{1}, \qquad \tau = 1, \dots, K. \tag{13}$$

with $\oslash$representing the element-by-element division. Given the multiplicative nature of the model $\rho_{t,\tau}^{(i)}$measures the set of response (relative changes) in the forecast profile beginning at time t for a horizon τ induced by 1 standard deviation shock in the ith market. Equation 13 allows us to observe the impacts of a normalized shock from one market to other markets. We pick May, 20, 2015, November, 4, 2015 and May, 5, 2016 as the starting dates t to see how the correlations of shocks change before, during and after the stock market crash, in order to analyse the impulse response functions (IRF) generated by the Chinese stock market. Impulse response functions allow us to describe how shocks in specific markets propagates to others.

Impulse response functions are shown in Figure 6 with the upper figure, middle and lower plotting impulse response function before, during and after the financial turbulence, respectively. The horizontal axis indicates the days since the shock hit the market, while the vertical axis identifies the volatility response, i.e., the relative difference between a baseline and the response after the shock. The Chinese markets experience a consistent behaviour before, during and after the crisis with respect to its own shocks. The trend is decreasing, with a non-uniform speed, due to high convexity. The response is higher than other markets given the volatility persistence in the market. From May, 20, 2015, meanwhile, Hong Kong, Singapore and Japan market reacts in a similar way to Shanghai, even if the magnitude is much smaller. Nigeria equity markets also experience an upsurge, but the highest shock is somehow delayed, quite reasonable if we consider geographical proximity. Impacts on Australia, UK and US markets seem to also be hump-shaped, but the impacting power seem to be very limited. During the outburst of the crisis, the impact of the Chinese stock market towards the other markets steadily goes up, reaching a peak and dropping rapidly shortly. At some point, due to this shock originated in China, investing in other countries becomes riskier. However, this shock, though large, as shown by the scale of the impulse response, and clearly felt by most countries, is reabsorbed by the most of them in few days. The only exception is given by Hong Kong, whose IRF is still hump-shaped. Moreover, it takes more days for Hong Kong to reabsorb the shock induced by the Chinese market. In the post-crisis period, the impulse response functions reveal a consistent picture with respect to the pre-crisis period.

[INSERT FIGURE 6 HERE]

In general, because many curves in Figure 6 would overlap, we need a synthesis of the impact of the shock from market i to market j at a specific date. We propose using the cumulative responses (the area under the curve) of country j to assess the total change caused by the shock:

$$\phi_t^{j,i} = \sum_{\tau=1}^{K} \rho_{t,\tau}^{j,i}. \tag{14}$$

We compute the cumulated responses for all markets and all days in the sample and report results that are averaged out as in Table 6. As one shown by previous results, mainland China as an originating market has the biggest impact on the Asian markets, supporting the idea of regional spillovers. Moreover, value by columns is different than value by rows, suggesting asymmetry of responses. Given that, we define the volatility spillover balance (VSB), an averaged index for all markets and all days, as:

$$VSB_i = \frac{\sum_{i \neq j} \sum_{t=1}^{T} \phi_t^{j,i}}{\sum_{i \neq j} \sum_{t=1}^{T} \phi_t^{i,j}}. \tag{15}$$

The volatility spillover balance determines the ratio of the of the average responses "from" to the average response "to" (excluding one's own), to evaluate total volatility. Depending on the value of VSB, a market can be defined as net creator or absorber of volatility: VSB_i greater than 1 implies that the market i is a net creator of volatility, while a value lower than 1 identifies countries that receive shocks but do not contribute to propagate.[22] In the pre-crisis period, over a period of 200 days, $T = 200$, and $K = 30$, the Chinese stock market is net receiver of volatility, $VSB_{CHN} = 0.6981$, while Hong Kong and Australia are fairly balanced, since their volatility spillover balance is almost equal to 1. More developed markets like US and Japan mainly act as net volatility spillover generators at the global and regional level.[23] Table 6 reports evidence of the global leading role of the United States. Before crisis, the US market, indeed, is a net volatility spillover generator with $VSB_{US} = 1.669V$ Empirical evidence also supports the view that the Hong Kong and Japan are net creator of in the region, since their volatility spillover balance are greater than 1. The other markets, instead, absorb volatility spillover. During the crisis, panel B in Table 6, the volatility spillover balance increases dramatically for the Chinese market, $VSB_{CHN} = 13.122$, shifting the role of the China from receiver net generator. Hong Kong changes its role to absorber, while Japan remains generator. Due to the

[22] As pointed out by Giovannetti and Velucchi (2013), the analysis of the volatility spillover balance should be combined with the significant interactions shown by the model. It may occur that a net creator of volatility does not have many interdependences in some region, and has a limited role in affecting other markets, even if propagating shocks.

[23] Rapach et al. (2013), indeed, find a dominant role of the US market, showing how return shocks arising in the United States are only fully reflected in equity prices outside of the United States with a lag.

local nature of spillovers, the US market remains a net generator of volatility spillovers even during, supporting that view that the Chinese stock market crisis is characterized by local spillovers, rather than global. Apart from Nigeria, other markets do not change its role in receiving or generating volatility. Panel C in Table 6 summarizes the volatility spillover balance after the financial turbulence. The Chinese stock market returns to the initial stage of volatility spillover receiver, with Hong Kong becoming generator. Both United States and Japan, experiencing its own financial turbulence, still act as volatility spillover generator. It is worth noting that United Kingdom acts as net creator of volatility due to the uncertainty created by Brexit.

[INSERT TABLE 6 HERE]

Figure 7 supports the empirical results provided in Table 6 by plotting the spillovers generated and received by the Chinese stock market, before, during and after crisis. This gives an exact picture of how the upsurge in volatility spillover balance for the Chinese market occurs with the extreme market conditions, and is not a result of macro conditions, since they are considered to be stable in the short run.

[INSERT FIGURE 7 HERE]

5. Conclusions

Despite having the world's second largest market capitalization, the Chinese stock market is still not fully developed and lacks a sufficiently transparent environment as well as sophisticated investors when compared to well-developed markets, which may amplify the transmission of potential risk.

This research studies the propagation of shocks originating in an economy whose distinctive features are capital controls and individual investors dominating the stock market. We use a multiplicative error model to capture the spillovers of five APAC equity markets (China, Hong Kong, Japan, Singapore and Australia) and three other countries (United States, United Kingdom and Nigeria) during the Chinese stock market crisis to model and describe whether (and how) volatility spills over from the Chinese market. We proxy market volatility with the daily range and define the dynamics of the expected volatility in a market including interactions with the past squared returns of other markets, allowing asymmetric effects and possible changes in the relationships across suitable sub-periods. We use dynamic volatility forecasts and impulse response functions to determines how financial markets reacts over time to shocks in the Chinese stock market. We summarize the volatility impacts to a one standard deviation from one market to another by a volatility spillover balance that determines if a country is net volatility generator or absorber.

We report that volatility spillovers generated from the Chinese stock market crisis tend to be regional rather than global, since China is an important trading partner and strategic financial centre on the Asia-Pacific region. The influence of the events in China plays a key role in APAC region, while it is less relevant for the UK and the US. Both volatility forecast and impulse responses confirm this view. Despite Hong Kong, all other market volatility responses have cumulative effects that takes time to be fully developed and are reabsorbed by the most of them in few days. The volatility spillover balance, constructed to measure the market either as a net volatility generator or net volatility receiver, shows how China market shifts from receiver to generator. We also, indirectly, provide evidence of the leading role of the US and Japanese market before, during and after the financial crisis.

Vice versa, Hong Kong experiences the opposite, encouraging open discussion about the impact of the Hong Hong-Shanghai stock connect.

From a practical perspective, our results are very important for asset allocation and portfolio optimization against the downside risk. The increased regional integration of mainland China should push both domestic and international investors to track the market movements and systematic risk. At the same time, the increased regional integration determines a complex scenario that policymakers should consider when implementing financial reforms and long-term economic policies

We believe that future research should indicate to which extent the Hong-Kong-Shanghai connect program increases regional integration and affects the dynamics of volatility spillover, allowing mainland China and Hong Kong to switch roles. Moreover, it should be determined how the Chinese stock market crisis has affected complex inter-industry interdependencies among different economies., i.e., how the financial turbulence spills over international sector industries or firms due to complex supply and value chains.

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Table 1: Daily range for the selected markets

	CHN	AUS	HK	JPN	NIG	SIN	UK	US
Whole Sample	1.040	0.630	0.727	0.766	0.633	0.534	0.798	0.685
Pre-crisis	0.961	0.605	0.703	0.734	0.623	0.510	0.789	0.710
Crisis	1.688	0.824	0.734	0.793	0.701	0.635	1.331	0.777
Post-crisis	0.741	0.609	0.674	0.861	0.595	0.580	0.761	0.506
S.D	0.7381	0.351	0.394	0.542	0.526	0.283	0.473	0.453
Minimum	0.229	0.126	0.165	0.145	0.000	0.126	0.146	0.126
Maximum	6.669	4.329	4.225	8.625	5.060	2.589	5.686	5.716
S.D	0.7381	0.351	0.394	0.542	0.526	0.283	0.473	0.453
Skewness	2.750	2.361	2.809	4.467	2.322	2.096	2.547	2.730
Kurtosis	13.956	14.906	18.233	42.239	12.496	9.925	16.436	18.183

Notes: This table reports the descriptive statistics for the annualized range, hl, for China (CHN), Australia (AUS), Hong Kong (HK), Nigeria (NIG), Singapore (SIN), United Kingdom (UK) and United States (US). Pre-crisis period goes from January, 1, 2010 to May, 11, 2015. Crisis period goes from May, 12, 2015 to January, 20, 2016. Post-crisis period goes from January, 21, 2016 to March, 3, 2017.

Table 2: Selected specification for each market

	CHN	AUS	HK	JPN	NIG	SIN	UK	US
Other markets	X	X	X	X	X	X	X	X
Other markets during crisis	X	X	X	X	X	X	X	X
Own asymmetric effects	X	X	X	X	X	X	X	X
Own asymmetries during crisis			X	X			X	X
Shift during crisis	X							
Shift after crisis	X					X	X	X
Lag 2 terms of own market				X	X			
Lag 2 terms of other markets		X	X					

Notes: This table reports the selection specification for China (CHN), Australia (AUS), Hong Kong (HK), Japan (JPN), Nigeria (NIG), Singapore (SIN), Taiwan (TA), Thailand (TH), United Kingdom (UK) and United Stated (US). A cross (X) indicates the presence of significant additional links relative to the own market (base) specification.

Table 3: Model diagnostics

Models	CHN-MEM(1,1)		HK-MEM(1,1)		JPN-MEM(2,1)		SIN-MEM(1,1)	
	Base	**Selected**	**Base**	**Selected**	**Base**	**Selected**	**Base**	**Selected**
Loglik	-2611.609	-2599.261	-2327.551	-2308.078	-2349.830	-2338.069	-2026.031	-2016.238
CORR(30)	19.860 (0.920)	14.729 (0.991)	33.216 (0.313)	38.337 (0.141)	37.083 (0.175)	38.606 (0.135)	52.925 (0.006)	41.393 (0.081)
CORRSQ(30)	18.725 (0.946)	13.547 (0.996)	29.679 (0.482)	31.416 (0.395)	25.472 (0.702)	25.791 (0.686)	53.277 (0.006)	39.638 (0.112)
$\hat{\phi}$		4.258		4.694		3.330		6.311
No spillovers		1.602 (0.130)		9.044*** (0.000)		1.404 (0.198)		4.505*** (0.000)
No spillovers added DC		4.201*** (0.000)		2.188** (0.032)		5.664*** (0.000)		3.759*** (0.000)

Models	AUS-MEM(1,1)		NIG-MEM(2,1)		UK-MEM(1,1)		US-MEM(1,1)	
	Base	**Selected**	**Base**	**Selected**	**Base**	**Selected**	**Base**	**Selected**
Loglik	-2176.842	-2158.250	-2162.984	-2150.119	-2379.593	-2369.471	-2219.987	-2211.394
CORR(30)	22.976 (0.816)	21.025 (0.887)	97.345 (0.000)	41.514 (0.079)	28.912 (0.522)	31.289 (0.401)	43.667 (0.051)	37.860 (0.153)
CORRSQ(30)	25.315 (0.710)	22.508 (0.835)	24.704 (0.739)	31.233 (0.404)	29.681 (0.482)	30.650 (0.433)	32.712 (0.335)	29.509 (0.491)
$\hat{\phi}$		5.262		1.683		5.714		5.089
No spillovers		16.010*** (0.000)		2.945*** (0.004)		4.672*** (0.000)		1.995 (0.052)
No spillovers added DC		1.728* (0.098)		1.871* (0.070)		1.446 (0.182)		0.804 (0.583)

Notes: This table indicates the order of the MEM estimated in both the base and the retained specifications for each market. LogLik is the value of the log likelihood. CORR(30) (respectively, CORRSQ(30)) is the LM test statistic for autocorrelation up to order 30 in the standardized residuals $\frac{h_t}{\hat{\mu}_t}$ (squared standardized residuals $\frac{h_t^2}{\mu_t^2}$, respectively) with the corresponding p-values in parentheses. $\hat{\phi}$ is the estimated method of moments gamma parameter. "No spillovers" and "No spillovers added DC" report the results of the Wald test statistics from imposing zero constraints on the interaction coefficients (whole period and extra interactions when present) and the corresponding p-values in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4: Coefficient estimation details

Models	CHN-MEM(1,1)		HK-MEM(1,1)		JPN-MEM(2,1)		SIN-MEM(1,1)	
	Base	Selected	Base	Selected	Base	Selected	Base	Selected
ω	0.028*** (0.000)	0.047*** (0.000)	0.041*** (0.000)	0.021*** (0.002)	0.025*** (0.000)	0.027*** (0.000)	0.012*** (0.000)	0.020*** (0.000)
μ_{t-1}	0.794*** (0.000)	0.762*** (0.000)	0.809*** (0.000)	0.879*** (0.000)	0.847*** (0.000)	0.888*** (0.000)	0.840*** (0.000)	0.732*** (0.000)
DC_{t-1}	- -	0.161* (0.056)	- -	- -	- -	- -	- -	- -
PC_{t-1}	- -	-0.019*** (0.008)	- -	- -	- -	- -	- -	0.017*** (0.000)
mkt_{t-1}^{+}	0.156*** (0.000)	0.150*** (0.000)	0.113*** (0.000)	0.05*** (0.000)	- -	0.259*** (0.000)	0.116*** (0.000)	0.114*** (0.000)
mkt_{t-1}^{-}	0.202*** (0.000)	0.197*** (0.000)	0.151*** (0.000)	0.065*** (0.000)	- -	0.301*** (0.000)	0.157*** (0.000)	0.150*** (0.000)
$mkt_{t-1}^{+}DC_{t-1}$	- -	- -	- -	-0.159*** (0.001)	- -	-0.235*** (0.000)	- -	- -
$mkt_{t-1}^{-}DC_{t-1}$	- -	- -	- -	0.0171 (0.714)	- -	-0.101*** (0.002)	- -	- -
CHN_{t-1}	- -	- -	- -	0.075*** (0.000)	-	-0.000 (0.970)	- -	0.003 (0.396)
$CHN_{t-1}DC_{t-1}$	- -	- -	- -	0.013 (0.356)	- -	0.004 (0.639)	- -	-0.008 (0.341)
AUS_{t-1}	- -	0.027 (0.281)	- -	0.014 (0.641)	- -	0.008 (0.520)	- -	0.003 (0.764)
$AUS_{t-1}DC_{t-1}$	- -	-0.321** (0.011)	- -	0.084* (0.085)	- -	-0.115*** (0.009)	- -	-0.033 (0.367)
HK_{t-1}	- -	-0.017 (0.398)	- -	- -	- -	-0.025*** (0.009)	- -	0.008 (0.402)
$HK_{t-1}DC_{t-1}$	- -	0.121* (0.093)	- -	- -	- -	0.011 (0.605)	- -	-0.003 (0.864)
JPN_{t-1}	- -	-0.004 (0.658)	- -	0.051*** (0.002)	0.325*** (0.000)	- -	- -	0.001 (0.702)
$JPN_{t-1}DC_{t-1}$	- -	-0.008 (0.932)	- -	-0.036 (0.239)	- -	- -	- -	-0.104*** (0.000)
NIG_{t-1}	- -	0.023** (0.016)	- -	-0.010 (0.528)	- -	0.006 (0.226)	- -	-0.002 (0.547)
$NIG_{t-1}DC_{t-1}$	- -	0.137 (0.228)	- -	0.009 (0.865)	- -	-0.006 (0.838)	- -	0.038 (0.269)
SIN_{t-1}	- -	-0.001 (0.976)	- -	0.239*** (0.000)	- -	0.002 (0.847)	- -	- -
$SIN_{t-1}DC_{t-1}$	-	0.120	-	-0.074*	-	0.106**	-	-

	-	(0.381)	-	(0.095)	-	(0.019)	-	-
UK_{t-1}	-	0.017	-	0.035	-	-0.003	-	0.014
	-	(0.379)	-	(0.229)	-	(0.766)	-	(0.207)
$UK_{t-1}DC_{t-1}$	-	-0.018	-	0.049	-	0.005	-	0.111**
	-	(0.903)	-	(0.463)	-	(0.896)	-	(0.017)
US_{t-1}	-	-0.018	-	0.055**	-	0.008	-	0.035***
	-	(0.346)	-	(0.048)	-	(0.381)	-	(0.001)
$US_{t-1}DC_{t-1}$	-	-0.131	-	-0.010	-	0.199***	-	0.026
	-	(0.524)	-	(0.903)	-	(0.009)	-	(0.644)
mkt_{t-2}	-	-	-	-	-0.206***	-0.200***	-	-
	-	-	-	-	(0.000)	(0.000)	-	-
CHN_{t-2}	-	-	-	-0.077***	-	-	-	-
	-	-		(0.000)	-	-	-	-
AUS_{t-2}	-	-	-	-0.001	-	-	-	-
	-	-	-	(0.949)	-	-	-	-
HK_{t-2}	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
JPN_{t-2}	-	-	-	-0.053***	-	-	-	-
	-	-	-	(0.002)	-	-	-	-
NIG_{t-2}	-	-	-	0.018	-	-	-	-
	-	-	-	(0.261)	-	-	-	-
SIN_{t-2}	-	-	-	-0.229***	-	-	-	-
	-	-	-	(0.000)	-	-	-	-
UK_{t-2}	-	-	-	-0.018	-	-	-	-
	-	-	-	(0.501)	-		-	-
US_{t-2}	-	-	-	-0.065**	-	-	-	-
	-	-	-	(0.020)	-	-	-	-

Notes: This table provides the coefficient estimates for the base and selected MEMs for China (CHN), Hong Kong (HK), Japan (JPN) and Singapore (SIN), January 2010-March 2017. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5: Coefficient estimation details

Models	AUS-MEM(1,1)		NIG-MEM(2,1)		UK-MEM(1,1)		US-MEM(1,1)	
	Base	Selected	Base	Selected	Base	Selected	Base	Selected
ω	0.023*** (0.000)	0.012*** (0.000)	0.012 (0.345)	-0.041 (0.149)	0.036*** (0.000)	0.016* (0.055)	0.037*** (0.000)	0.031*** (0.000)
μ_{t-1}	0.857*** (0.000)	0.891*** (0.000)	0.774*** (0.000)	0.678*** (0.000)	0.779*** (0.000)	0.718*** (0.000)	0.749*** (0.000)	0.750*** (0.000)
DC_{t-1}	- -	- -	- -	- -	- -	- -	- -	- -
PC_{t-1}	- -	- -	- -	- -	- -	0.013 ** (0.035)	- -	-0.016*** (0.000)
mkt_{t-1}^{+}	0.054*** (0.000)	0.016 (0.191)	- -	0.421*** (0.000)	0.112*** (0.000)	0.068* (0.079)	0.119*** (0.000)	0.077*** (0.000)
mkt_{t-1}^{-}	0.155*** (0.000)	0.080*** (0.000)	- -	0.430*** (0.000)	0.236*** (0.000)	0.181*** (0.000)	0.274*** (0.000)	0.225*** (0.000)
$mkt_{t-1}^{+}DC_{t-1}$	- -	- -	- -	- -	- -	-0.230** (0.013)	- -	-0.146* (0.066)
$mkt_{t-1}^{-}DC_{t-1}$	- -	- -	- -	- -	- -	-0.168* (0.063)	- -	-0.001 (0.981)
CHN_{t-1}	- -	0.007 (0.514)	- -	0.005 (0.615)	- -	0.011 (0.100)	- -	0.003 (0.536)
$CHN_{t-1}DC_{t-1}$	- -	0.011 (0.102)	- -	0.011 (0.354)	- -	-0.003 (0.804)	-	-0.004 (0.670)
AUS_{t-1}	- -	- -	- -	0.025* (0.092)	- -	0.012 (0.576)	- -	0.014 (0.386)
$AUS_{t-1}DC_{t-1}$	- -	- -	- -	0.126* (0.057)	- -	0.067 (0.172)	- -	0.046 (0.287)
HK_{t-1}	- -	0.019 (0.276)	- -	-0.008 (0.472)	- -	0.008 (0.525)	- -	-0.0129 (0.297)
$HK_{t-1}DC_{t-1}$	- -	-0.041* (0.061)	- -	-0.038 (0.179)	- -	-0.032 (0.342)	- -	0.003 (0.889)
JPN_{t-1}	- -	0.010 (0.521)	- -	0.031** (0.045)	- -	0.002 (0.741)	- -	-0.011** (0.046)
$JPN_{t-1}DC_{t-1}$	- -	0.005 (0.786)	- -	-0.066 (0.224)	- -	-0.066* (0.098)	- -	0.007 (0.823)
NIG_{t-1}	- -	0.023 (0.123)	0.440*** (0.000)	- -	- -	0.010 (0.258)	- -	0.000 (0.906)
$NIG_{t-1}DC_{t-1}$	- -	0.003 (0.861)	- -	- -	- -	0.032 (0.483)	- -	0.057* (0.053)
SIN_{t-1}	- -	-0.022 (0.448)	- -	-0.020** (0.044)	- -	0.015 (0.438)	- -	0.044** (0.013)
$SIN_{t-1}DC_{t-1}$	- -	-0.019 (0.475)	- -	0.103 (0.133)	- -	0.064 (0.216)	- -	-0.006 (0.8784)

UK_{t-1}	- -	0.063*** (0.005)	- -	0.046 (0.149)	- -	- -	- -	0.025 (0.132)
$UK_{t-1}DC_{t-1}$	- -	0.091** (0.018)	- -	-0.185** (0.020)	- -	- -	- -	-0.036 (0.554)
US_{t-1}	- -	0.249*** (0.000)	- -	-0.001 (0.819)	- -	0.093*** (0.000)	- -	- -
$US_{t-1}DC_{t-1}$	- -	-0.067 (0.129)	- -	0.071 (0.492)	- -	0.184* (0.064)	- -	- -
mkt_{t-2}	- -	- -	-0.2276*** (0.000)	-0.119*** (0.003)	- -	- -	- -	- -
CHN_{t-2}	- -	-0.004 (0.649)	- -	- -	- -	- -	- -	- -
AUS_{t-2}	- -	- -	- -	- -	- -	- -	- -	- -
HK_{t-2}	- -	-0.025 (0.875)	- -	- -	- -	- -	- -	- -
JPN_{t-2}	- -	-0.009 (0.226)	- -	- -	- -	- -	- -	- -
NIG_{t-2}	- -	-0.018 (0.226)	- -	- -	- -	- -	- -	- -
SIN_{t-2}	- -	0.043 (0.154)	- -	- -	- -	- -	- -	- -
UK_{t-2}	- -	-0.059*** (0.006)	- -	- -	- -	- -	- -	- -
US_{t-2}	- -	-0.236*** (0.000)	- -	- -	- -	- -	- -	- -

Notes: This table provides the coefficient estimates for the base and selected MEMs for Australia (AUS), Nigeria (NIG), United States (US) and United Kingdom (UK), January 2010-March 2017. *p*-values are in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: Summary of the Volatility Impacts to a One-Standard Deviation Shock to the Market

Panel A: Volatility impacts before the crisis								
From \ To	**CHN**	**AUS**	**HK**	**JPN**	**NIG**	**SIN**	**UK**	**US**
CHN	6.395	1.089	0.883	0.438	4.205	0.056	0.722	0.104
AUS	0.748	5.501	0.647	0.187	2.436	0.789	0.789	1.806
HK	0.482	1.014	5.345	0.402	2.652	0.451	1.009	0.597
JPN	0.05	0.607	2.798	11.348	2.182	0.009	0.121	0.738
NIG	1.371	2.286	1.753	4.603	19.977	0.277	2.495	1.729
SIN	0.746	0.563	0.274	0.191	0.114	2.827	0.872	2.053
UK	1.102	0.892	0.119	0.008	2.222	0.623	2.900	2.606
US	0.732	0.808	0.488	1.141	0.546	1.003	1.053	4.736
VSB	***0.698***	***0.981***	***1.053***	***1.071***	***0.989***	***0.667***	***0.932***	***1.669***
Panel B: Volatility impacts during the crisis								
From \ To	**CHN**	**AUS**	**HK**	**JPN**	**NIG**	**SIN**	**UK**	**US**
CHN	5.649	0.359	0.775	1.625	8.393	1.252	0.794	1.528
AUS	22.231	104.409	31.020	72.776	37.796	48.601	72.901	42.948
HK	26.840	20.610	4.793	25.246	42.740	7.947	24.275	57.798
JPN	4.928	12.650	6.288	12.140	23.099	9.807	10.119	6.278
NIG	55.91	68.925	36.587	66.030	181.789	51.433	60.711	52.351
SIN	33.349	101.580	39.435	136.446	160.350	70.902	81.634	58.171
UK	30.098	54.953	25.689	64.701	126.608	42.097	53.089	55.007
US	19.926	38.1824	17.300	40.945	65.234	27.041	31.305	29.630
VSB	***13.122***	***0.906***	***0.765***	***5.572***	***1.184***	***0.308***	***0.706***	***1.142***
Panel C: Volatility impacts after the crisis								
From \ To	**CHN**	**AUS**	**HK**	**JPN**	**NIG**	**SIN**	**UK**	**US**
CHN	5.981	1.701	1.424	0.769	4.131	0.121	1.119	0.122
AUS	0.432	5.534	0.675	0.216	1.548	1.059	0.789	1.457
HK	0.261	0.961	5.249	0.438	1.591	0.570	0.948	0.452
JPN	0.0243	0.569	2.702	12.119	1.323	0.009	0.110	0.561
NIG	1.259	3.609	2.821	8.515	20.681	0.574	3.883	2.192
SIN	0.335	0.447	0.221	0.176	0.061	2.927	0.687	1.307
UK	0.632	0.896	0.123	0.009	1.398	0.833	2.897	2.107
US	0.509	0.988	0.614	1.590	0.412	1.638	1.286	4.696
VSB	***0.368***	***1.484***	***1.643***	***2.208***	***0.458***	***1.486***	***1.471***	***1.165***

Notes: This table reports the average cumulated effect of a 1 standard deviation shock from the market by column to each market by row, before, during and after the stock market crisis (Panel A, B and C, respectively). The last row, in each panel, reports the volatility spillover balance (VSB) of market i as the ratio of the sum by column ("From") to the ratio of the sum by row ("To"), excluding element (i, i).

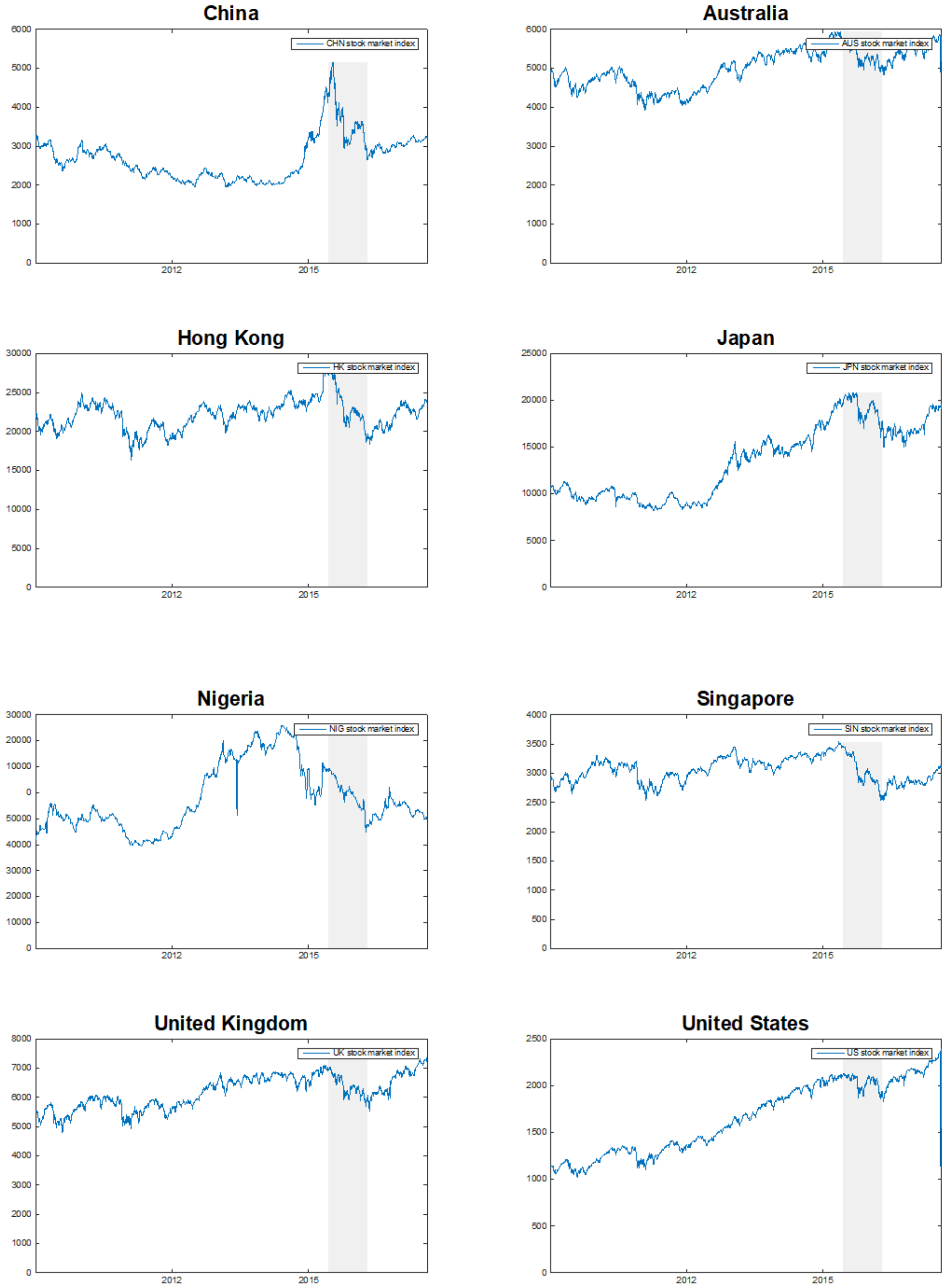

Figure 1: Stock Indices, January 2010 - March 2017. The shaded area identifies the crisis period: June, 12, 2015 - January, 28, 2016.

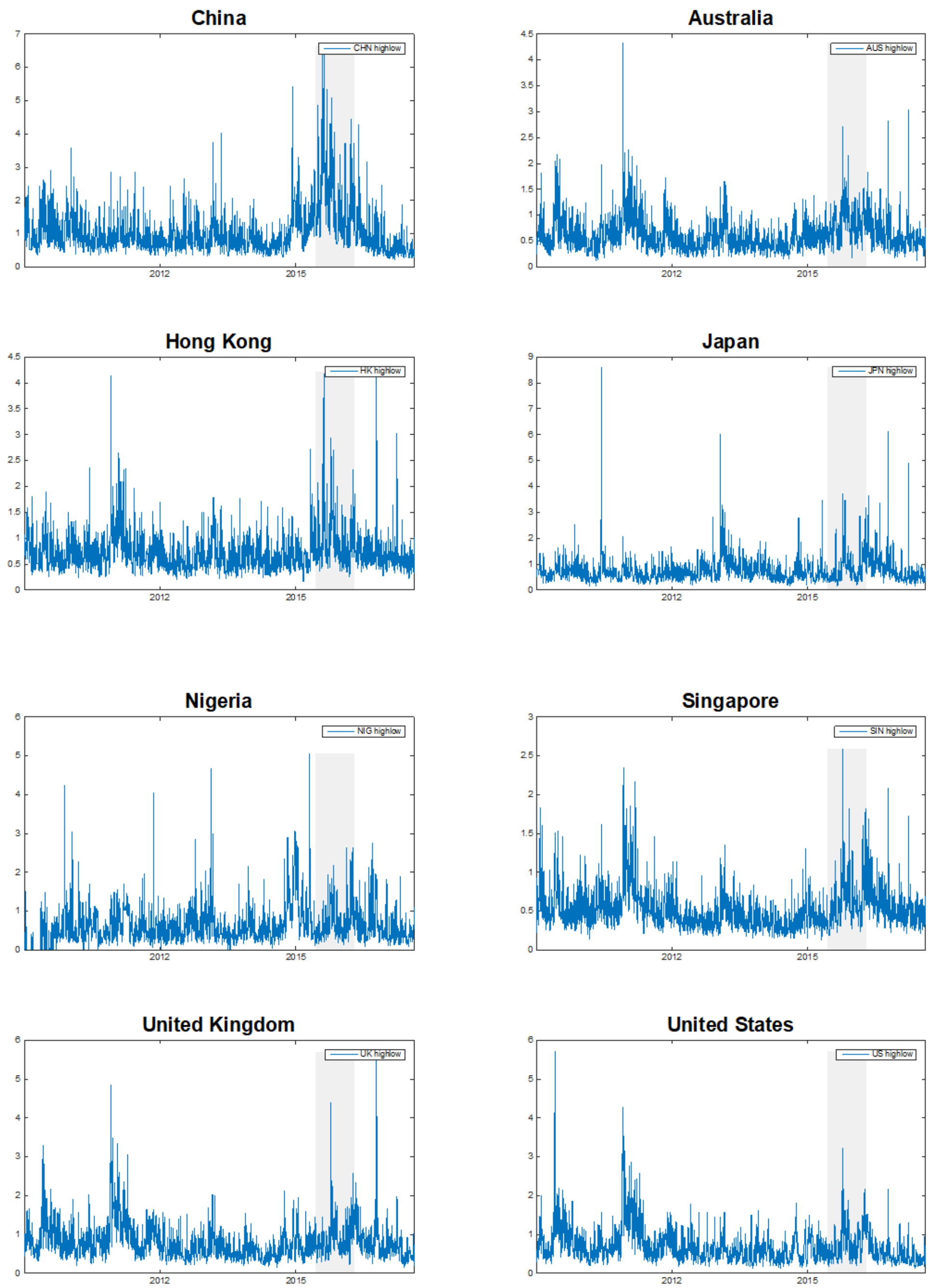

Figure 2: hl_t for all markets, January 2010 - March 2017. The shaded area identifies the crisis period: June, 12, 2015 - January, 28, 2016.

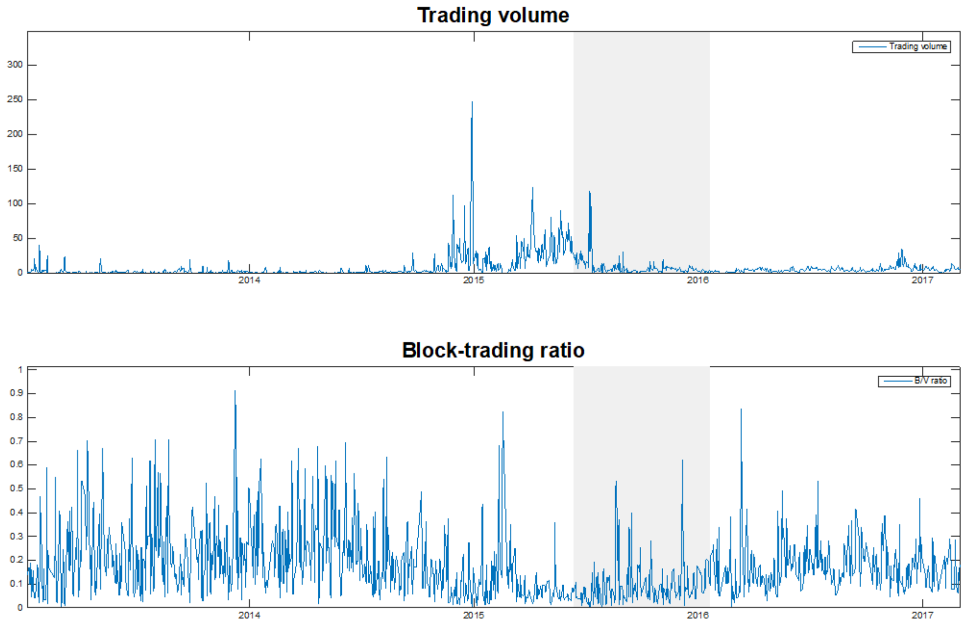

Figure 3: Total trading volume, upper figure, and block trading ratio, lower figure, for the Chinese stock market, November 2013 - March 2017. The shaded area identifies the crisis period: June, 12, 2015 - January, 28, 2016.

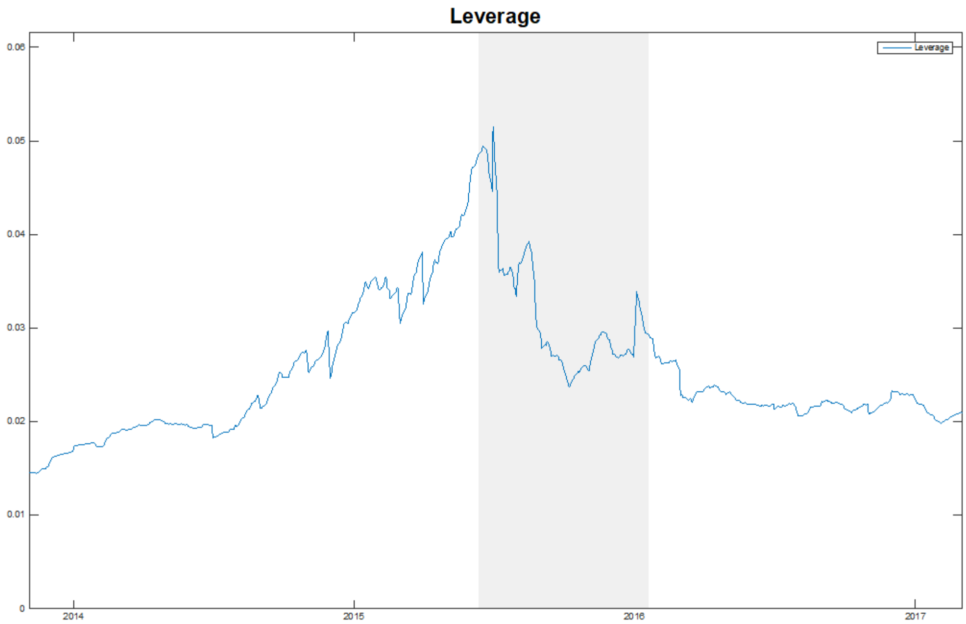

Figure 4: Leverage, measured as margin balance over free-float market cap, November 2013 - March 2017. The shaded area identifies the crisis period: June, 12, 2015 - January, 28, 2016.

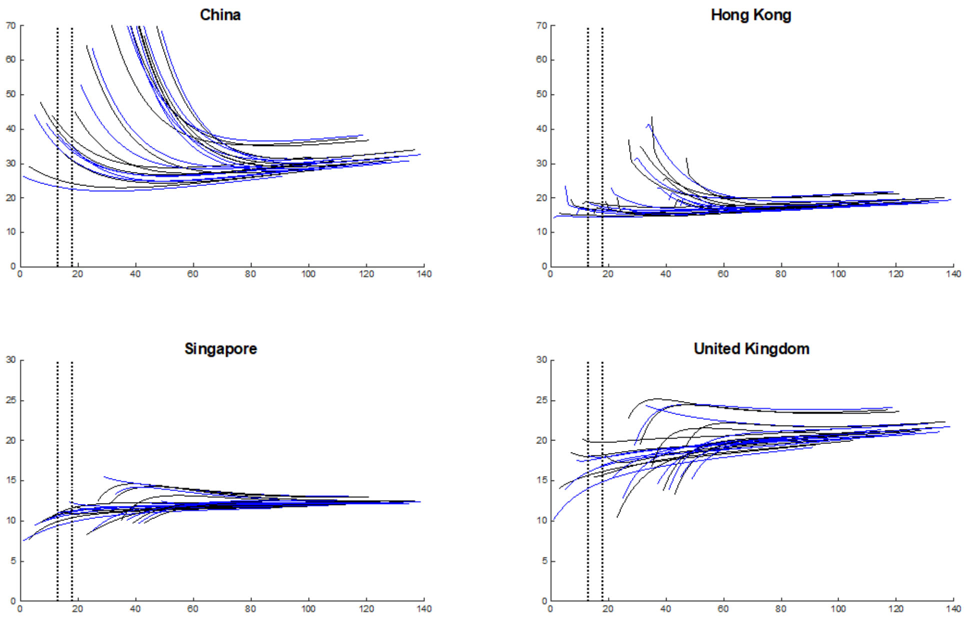

Figure 5: Dynamic Volatility Forecasts on China, Hong Kong, Singapore and United Kingdom, computed according to equations 7 and 8. Starting from May, 12, 2015, and progressively moving the initial condition ahead.

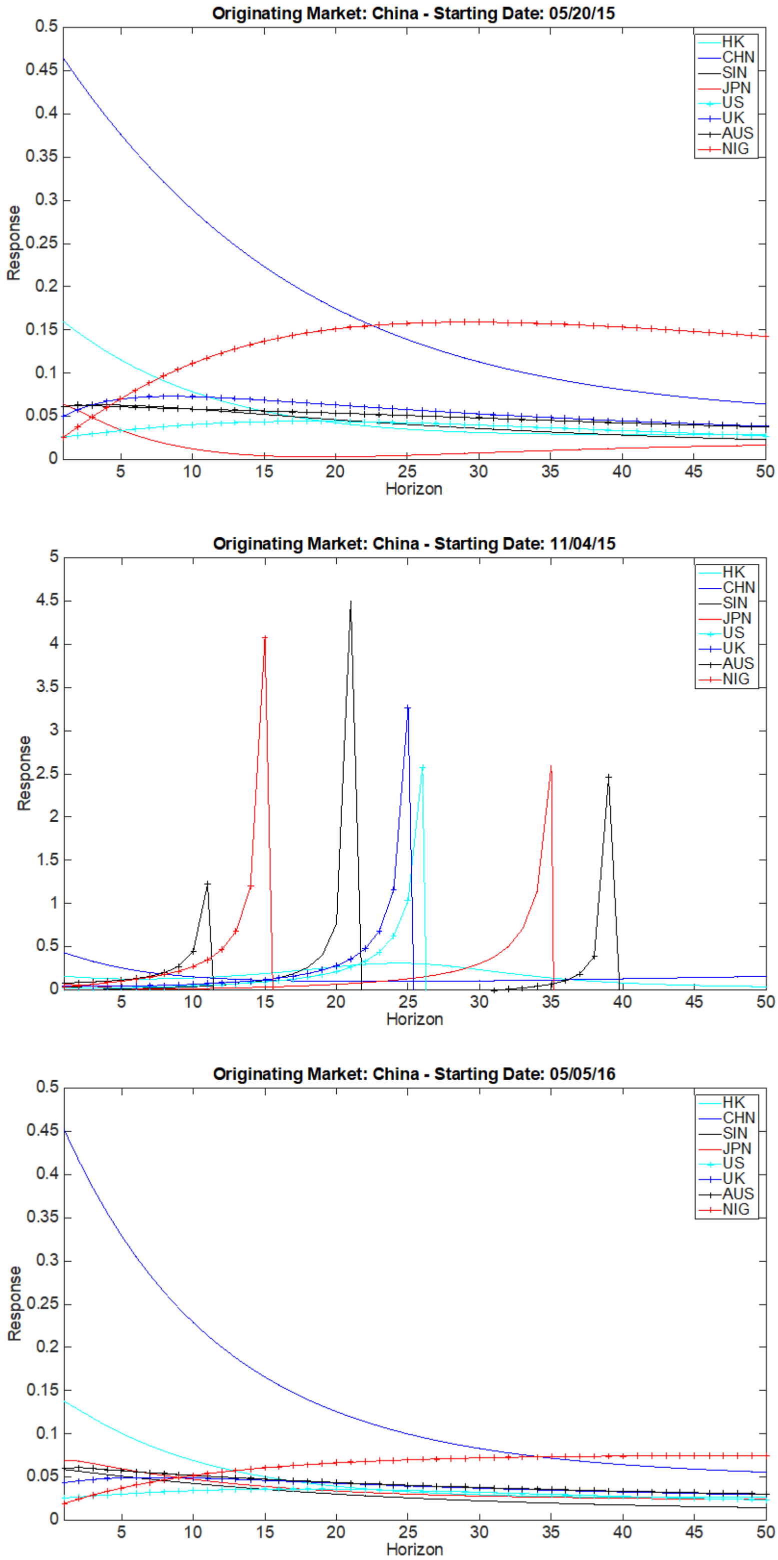

Figure 6: MEM impulse response functions with China as originating market. Each line shows the markets' relative response to shock originating in China before, during and after the crisis (upper, middle and lower figure), respectively.

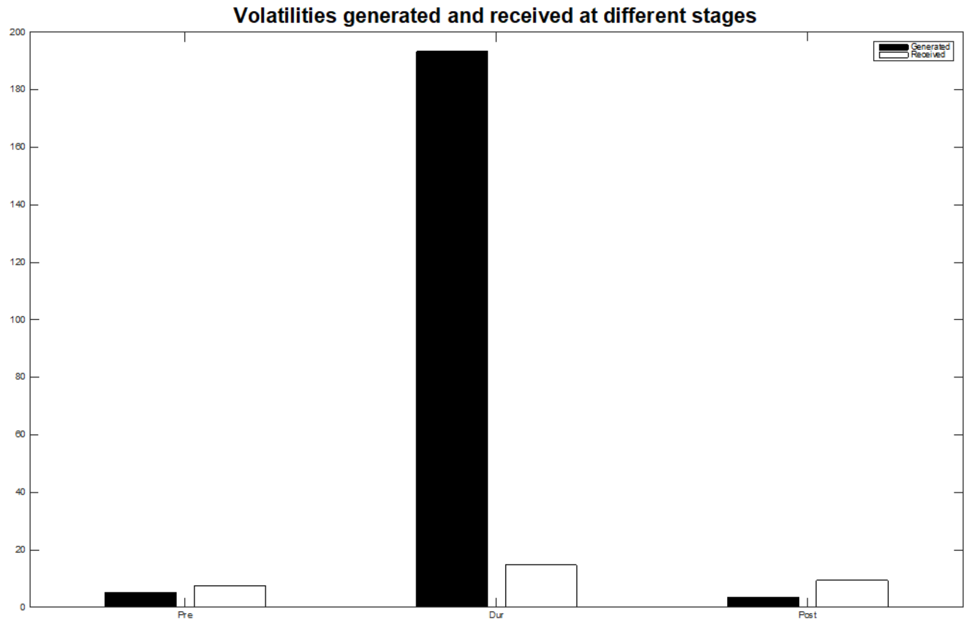

Figure 7: Volatilities generated (black bar) and received (white bar) by the Chinese market before (Pre), during (Dur) and after (Post) the crisis.