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Abstract

This paper examines time-varying price discovery of the Chinese stock index futures market during a stock market crash in 2015. We find that the index futures market plays a long-run leading role in terms of its higher static and dynamic generalised information share (GIS) than both the Shanghai and Shenzhen A share markets during the market turbulence. The expected trading volume in each market improves GIS of that market. The importance of trading activities by the majority of investors in increasing market efficiency during a crash is underscored. Government intervention on futures trading impairs price discovery in the futures market.

JEL classifications: G13; G14; G15

Keywords: Generalised Information Share, Price Discovery, GARCH model, Chinese stock market crash, Chinese stock index futures

1. Introduction

As the Chinese economy has dramatically grown in recent years, its security markets play a significant role in the integration of the global financial markets (Yang et al., 2012; Chen et al., 2013). Their effects on the global markets have important implications for international financial institutions and practitioners. Moreover, the Chinese equity markets operate under special circumstances and differ substantially from the index futures markets in terms of security supplies, trading mechanism, and investor structure (Chen et al., 2013)[1]. These differences imply that the index futures market may be superior to the underlying spot market in terms of information content since the former has smaller transaction costs and less market microstructure biases (Flemming et al., 1996).

However, it is well acknowledged that the index futures market in China is still immature and as such is being stringently monitored by local market regulators (Yang et al., 2012; Chen et al., 2013). Information content of futures prices may thus be impeded by the strict trading regulations and high barriers of entry[2]. Hence the classical transaction cost hypothesis may not entirely apply to China. Although a limited number of studies have examined price discovery efficiency of the Chinese stock index futures market in recent years, the conclusion remains controversial. Yang et al. (2012) find that the Chinese stock index futures market is overshadowed by the equity market in the long run at the nascent stage of the former. Nonetheless, Guo et al. (2013) and Hou and Li (2013, 2015) reveal that the price discovery performance of the index futures market in China has improved since its inception. This is supported by Xu and Wan (2015)

[1] Please see detailed characteristics of the Chinse stock index futures market in Appendix 1.
[2] The strict trading regulations result in a small number of market participants, limited types of trading strategies, and limited types of investment funds that involve index futures contracts.

who find similar evidence on the time-varying price discovery performance of the index futures market[3].

The recent crash in the Chinese stock market on June 12, 2015 has re-ignited interest in the performance of the Chinese stock index futures market[4]. Though the reasons given for the trigger to the crisis vary, a common view is that the crash began after a set of huge declines in the prices of the most heavily traded CSI 300 index futures contracts. This has raised serious doubts by the Chinese regulators, practitioners and academics about the functionality of index futures. Nonetheless, Han and Liang (2017) stress the importance of index futures trading as its termination substantially deteriorates the quality of the underlying spot market during a market crash. Previous to this Chen et al. (2013) conclude, using a panel data approach, that the introduction of index futures provides a stabilising effect on the underlying spot market in a tranquil period. However, Xie and Mo (2014) report a short-run destabilising effect of index futures on the volatility of the spot market. Hence, the debate on the informational effects of the Chinese stock index futures on the underlying stock market continues as conclusions remain mixed.

This paper delves into this issue by examining the static and time-varying price discovery performance of the Chinese stock index futures relative to two A share indices in China - the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) A share index, during the market crash of 2015. A recently developed generalised information share (GIS) measure by Lien and Shrestha (2014) is employed for the study[5]. GIS is adopted since not only does it yield a

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[3] Some details on the Chinese stock index futures markets are provided in Appendix 1.

[4] Before the crisis took place, the Chinese stock market had kept increasing since the beginning of 2015. During the period between June 12 and August 6, 2015, the maximal drop of the Shanghai stock exchange was close to 34.9% while that of the Shenzhen stock exchange was almost 40%. The two markets kept destabilised till August 24, 2015. On that date they suffered from another round of hits where the Shanghai and Shenzhen stock markets dropped by 8.49% and 7.83%, respectively. See details of the market crash in Han and Liang (2017).

[5] Lien and Wang (2016) compare GP information share with MIS. They conclude that MIS is superior to Gramming and Peter's information share because the former provides at most marginal improvement over the method based upon the upper /lower bound midpoint of the Hasbrouck information share. As such, one could believe GIS may be superior

unique measure of information share but also applies to the situation where the cointegrating relation is not one-to-one[6]. We estimate both the static and time-variant GIS measures of each pair of A share indices and index futures using high-frequency data sampled at 1-minute intervals[7]. Moreover, we also explore the effect of regulatory intervention on index futures trading and how different components of trading volume affect GIS of the index futures prices during the market crash.

The SSE A share index and SZSE A share index, were established to reflect the overall performance of the Shanghai and Shenzhen share markets, respectively, with each index comprising all the A-shares traded in their exchange. In contrast, the CSI 300 index that was created on April 8th, 2005 covers only the 300 heavily-capitalised A share stocks traded in both Shanghai and Shenzhen stock exchanges. Thus the SSE and SZSE A share indices are expected to provide a better picture of the overall performance of A share markets in China than the standalone CSI 300 index. Examining the information assimilation process between index futures and A share indices sheds light on price discovery of the former market relative to non-component A share stocks.

Time variation of GIS is achieved by employing a vector error correction (VEC) asymmetric generalised dynamics conditional correlation (AG-DCC) GARCH model. Compared to other specifications of the multivariate GARCH models such as BEKK, CCC, and DCC, the AG-DCC

to Gramming and Peter's information share since MIS is a special case of GIS. Hence we focus on GIS only for analysis in this paper.

[6] Correlations between the Chinese A-share stock indices and index futures are high on average, suggesting the traditional IS may not be appropriate for the study. Also, the one-to-one cointegrating relation is rejected as suggested by our analysis.

[7] Baillie et al. (2002) demonstrate that the mean of the lower and upper bounds of Hasbrouck information share is a reasonable measure of price discovery. The mid-point of the upper and lower bounds of the IS measure is accepted in Hasbrouck (2003), Chakravarty et al. (2004), Ates and Wang (2005), Chen and Gau (2009, 2010), Xu and Wan (2015), among others. However, Lien and Shrestha (2009) point out that the average seems to be arbitrary since it cannot be shown to be result of any particular factor structure. In addition, for the average IS of more than two markets, the sum of them would not necessarily be 100%.

specification can simultaneously estimate both the individual conditional variances and the asymmetric conditional correlations (Cappiello et al., 2006). Moreover, the time-varying GIS series are computed taking into account return skewness. Utilising a skewed probability density for the estimation of a multivariate GARCH model improves the quality of forecasting results than a symmetric density by introducing additional flexibility for modelling the time series of asset returns with multivariate volatility models (Bauwens and Laurent, 2005).

Note that we use a bivariate instead of a trivariate model system to gauge GIS measures for the price discovery process between each A-share stock index and index futures. This is because the bivariate model enables us to respectively investigate the effects of the index futures on the two local stock markets, which is a major focus of this paper[8].

The contributions of the paper are three-fold. First, as the stock index futures market is designed to provide informational channels to the underlying spot market, its performance in terms of its informational role in a market crash event has attracted increased attention. The literature on the behaviour of the stock index futures market in the market crisis is scarce and conclusions remain mixed. Some evidence suggests a malfunction of the market during the crisis, which includes a significant negative mispricing (Draper and Fung, 2003; Hassan et al., 2007), a delinkage with the underlying spot market (Kleidon and Whaley, 1992), and a destabilising effect stemming from futures trading activities (Ghysels and Seon, 2005). There is also evidence of a disintegration of international stock index futures markets (Karim et al., 2011). In contrast, there is also evidence of continued performance of the futures market in crisis periods given its short-run leading role in price discovery (Harris, 1989) and a decline in arbitrage profits (Cheng et al., 2000). These findings, however, do not clearly show the long-run informational role of the futures

[8] We also obtain the results from a trivariate model system. They are consistent with those of the bivariate model. Relevant results are shown in Appendix 5.

market in the crash. This paper complements the evidence by examining information share of the stock index futures during a recent stock market crash in a typically fast-transiting economy. The results shed light on the pricing behaviour of the stock index futures prices under extreme circumstances of an order-driven market. We find that the index futures market plays a long-run leading role in terms of its higher static and dynamic generalised information share (GIS) than both the Shanghai and Shenzhen A share markets during the market turbulence.

Second, this paper complements evidence regarding the effects of trading volume by different groups of investors on price discovery of stock index futures prices during the market crash. The literature has revealed that the expected and unexpected trading volume, which respectively represents trading activities by major and minor but informed investors in the market, significantly affects market volatility (Bessembinder and Seguin, 1993; Martinez and Tse, 2008). Although trading volume is found to aggregately relate to information share in the stock and foreign exchange markets (Chen and Gau, 2009, 2010; Xu and Wan, 2015), the question of whether different components of trading volume directly contribute to information content remains unresolved. This paper addresses this question by exploring whether the expected and unexpected trading volume drives time-varying GIS in the Chinese A share stock and stock index futures markets when the markets are in turbulence. We find that the expected volume in each market improves its GIS while the unexpected volume rarely affects it. This finding highlights the importance of trading activities by the major investors during a market crash that their trading activities help to improve information content of security prices. This enriches our understanding of the relationship between trading activities of market participants and information content of security prices.

Last, there is mixed evidence in the literature regarding the efficacy of government intervention during market turbulence. Some argue that government intervention helps to stabilise the stock market and restore market efficiency (Cheng et al., 2000; Su et al., 2002) while others suggest the reverse (Kleidon and Whaley, 1992; Draper and Fung, 2003; Khan and Batteau, 2011). Han and Liang (2017) investigate the recent stock market crash in China and find that a series of announcements made by the Chinese Securities Regulatory Committee (CRSC) which almost terminated the trading of index futures contracts during the crash, in fact caused the quality of information from the underlying spot market to deteriorate. This study complements the analysis by Han and Liang (2017) by focussing attention on the effects of those announcements on price discovery in the futures market. We find that regulatory intervention significantly downgrades the price discovery performance of the local index futures market. The finding does not support the government's discretional market intervention thereby enriching the evidence on the government's role in financial crises.

The remainder of this paper is organised as follows. Section 2 presents the methods while section 3 shows the data and some sample statistics. Empirical results are summarised in Section 4. Section 5 concludes.

2. Methods

2.1. Generalised Information Share

Let Y_t be an $n \times 1$ vector of $I(1)$ series and assume that there exist n - 1 cointegrating vectors; that is, Y_t contains a single common stochastic trend (Stock and Watson, 1988)[9]. Then Y_t can be specified in the following vector error correction model (VECM) (Engle and Granger, 1987):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t. \tag{1}$$

where $\Pi = \alpha\beta^T$.

Following Stock and Watson (1988) and Hasbrouck (1995), Equation (1) can be transformed into the following vector moving average (VMA) model:

$$Y_t = Y_0 + \Psi(1) \sum_{i=1}^{t} \varepsilon_i + \Psi^*(L)\varepsilon_t. \tag{2}$$

When the cointegrating relationships are not one-to-one, rows of $\Psi(1)$ are not identical. Let ψ_i^g be the ith row of $\Psi(1)$. According to Lien and Shrestha (2014), when the innovations are independent, the contribution of the innovation of series j to the total variance of the common factor of series i is then represented by

$$S_{j,i}^G = \frac{\psi_{1j}^2 \Omega_{jj}}{\psi_1^g \Omega \psi_1^{g^T}}. \tag{3}$$

where ψ_{ij} is the jth element of the row vector ψ_i^g and hence ψ_{1j} is the jth element of the row vector ψ_1^g. Ω is a covariance matrix of innovations which is diagonal. $S_{j,i}^G$ is the so called generalised information share (GIS) of series j which is independent of i.

When the innovations are not independent, the GIS of series j can be calculated as

[9] Note that n equals to 2 in this study.

$$S_j^G = \frac{(\psi_j^G)^2}{\psi_1^g \Omega \psi_1^{g^T}}. \tag{4}$$

where $\psi^G = \psi_1^g F^g, F^g = \hat{F} = [G\Lambda^{-1/2}G^T V^{-1}]^{-1}$, and ψ_j^G is the jth element of ψ^G . Λ is a diagonal matrix where the eigenvalues of the correlation matrix of innovations are on the diagonal and the corresponding eigenvectors are the column vectors of matrix G. V is a matrix containing the standard deviations of innovations on the diagonal. Then we have $\Omega = \hat{F}\hat{F}^T$. It should be noted that the GIS measure yields a unique result given the factorization matrix $\hat{F}$.

2.2. Asymmetric Generalised DCC GARCH Model

It is well acknowledged that the covariance matrix of innovations in Equation (1) should be conditioned on past information (Bollerslev, 1990; Engle and Kroner, 1995; Engle, 2002). This is in accordance with the phenomenon of volatility clustering observed for unit-root series Y_t where large returns follow large ones while small returns are in tandem with small ones across time. To explore the time-varying nature of the information generation process, this study employs a bivariate asymmetric generalised DCC GARCH model proposed by Cappiello et al. (2006) to specify the individual heteroscedastic processes as well as the conditional correlation matrix of innovations.

Specifically, in the bivariate AG-DCC GARCH model, the error structure of Equation (1) is specified as

$$\varepsilon_t | \Xi_{t-1} \sim F(0, H_t). \tag{5}$$

where $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]^T$ is a 2×1 vector. Ξ_{t-1} represents the information set up to t-1. F denotes a bivariate distribution. H_t is a 2×2 positive-definite conditional covariance matrix and it can be decomposed as

$$H_t = D_t R_t D_t, \quad (6)$$

with

$$D_t = diag\{h_{11,t}^{\frac{1}{2}}, h_{22,t}^{\frac{1}{2}}\}, \quad (7)$$

and

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2}. \quad (8)$$

where D_t is a 2×2 diagonal matrix containing the square root of individual conditional heteroscedastic processes $h_{ii,t}$ $(i = 1,2)$ on the diagonal; R_t is the conditional correlation matrix of innovations ε_t constituted by the conditional covariance of standardized innovations (Q_t) where standardized innovations $\epsilon_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{ii,t}}} (i = 1,2)$.

The individual conditional variance is specified in an exponential GARCH (1, 1) model proposed by Nelson (1991) that is shown as

$$\log(h_{ii,t}) = \alpha_{1i} + \alpha_{2i} \left| \frac{\varepsilon_{i,t-1}}{\sqrt{h_{ii,t-1}}} \right| + \alpha_{3i} \frac{\varepsilon_{i,t-1}}{\sqrt{h_{ii,t-1}}} + \alpha_{4i} \log\left(h_{ii,t-1}\right). \quad (9)$$

where *i* =1,2. In Equation (9), the conditional variance $h_{ii,t}$ is guaranteed to be positive during the estimation process regardless of the values of the coefficients. Parameter α_{2i} measures the size effect and theoretically should be positive, as a shock with higher absolute value should have stronger effect on volatility. Moreover, the model allows to simultaneously estimate the asymmetric effects of positive and negative lagged values of $\varepsilon_{i,t}$ to the conditional variances. The effects are captured by parameter α_{3i}. We expect α_{3i} to be negative since a negative shock has a stronger effect on volatility than an equally positive shock. Note that for $h_{ii,t}$ to be stationary, α_{4i} should be less than 1.

According to Cappiello et al. (2006), Q_t in Equation (8) is specified as

$$Q_t = (\bar{R} - A^T\bar{R}A - B^T\bar{R}B - G^T\bar{S}G) + A^T\epsilon_{t-1}\epsilon_{t-1}^T A + B^T Q_{t-1}B + G^T s_{t-1}s_{t-1}^T G. \qquad (10)$$

where A, B and G are 2×2 diagonal matrices with coefficients a_{ii}, b_{ii} and g_{ii} (i = 1,2) on the diagonal. ϵ_t is a 2×1 vector of standardized innovations where $\epsilon_t = [\epsilon_{1,t}, \epsilon_{2,t}]^T$. $s_t = I_t \odot \epsilon_t$ where I_t is a 2×1 indicator function which equals to 1 if $\epsilon_t < 0$ and 0 otherwise. $\odot$ is the element-by-element operator. $\bar{R} = E[\,\epsilon_t\,\epsilon_t^T]$ represents the unconditional covariance of ϵ_t. $\bar{S} = E[s_t\, s_t^T]$.

Equation (10) is referred to as the asymmetric generalized DCC (AG-DCC) where the asymmetry in correlation of innovations is captured by the term $G^T s_{t-1}s_{t-1}^T G$. For Q_t to be positive definite, a sufficient condition requires that the intercept, $\bar{R} - A^T\bar{R}A - B^T\bar{R}B - G^T\bar{S}G$, is positive semi-definite and the initial covariance matrix Q_0 is positive definite. Note that the asymmetric DCC (A-DCC) is a special case of the AG-DCC where A, B and G are replaced by scalars. We propose a diagonal version of the AG-DCC in this study since it can sufficiently reduce the number of parameters that convey little information and thus alleviate the computation burden of estimation process. In addition, the diagonal model is preferred by applications to a small number of assets (Cappiello et al., 2006)[10].

We can compute the time-varying IS and GIS measures by replacing the time-invariant covariance matrix Ω of innovations with its conditional counterpart H_t obtained by Equation (6), similar to Avino et al. (2015). We assume that adjustment coefficients are constant over the sample period in the calculation.

[10] The estimation method on the AGDCC GARCH model is shown in Appendix 2.

2.3. Multiple Regression Model

After obtaining the estimated conditional GIS measure, we investigate how price discovery in the index futures market varies with market dynamics during the market crash in China. Since the conditional GIS is computed for each pair of markets, we typically explore how the GIS of the futures market relative to its A share counterpart reflects multiple market variables[11]. The regression model is shown as

$$\frac{GIS_{f,t}}{GIS_{s,t}} = \beta_0 + \gamma D_t + \beta_1 \frac{EV_{f,t}}{EV_{s,t}} + \beta_2 \frac{UnEV_{f,t}}{UnEV_{s,t}} + \beta_3 \frac{\sigma_{f,t}}{\sigma_{s,t}} + \beta_4 \frac{NoTrade_{f,t}}{NoTrade_{s,t}} + e_t. \tag{11}$$

where $GIS_{f,t}$ and $GIS_{s,t}$ represent the conditional GIS for the futures and A share stock markets at time t, respectively[12]. The dependent variable of Equation (11) is a time-varying relative ratio of the price discovery performance between each pair of markets[13]. D_t is a dummy variable taking the value of 1 on and after August 25, 2015 where a series of announcements were made to restrict speculative trading in the index futures market and thereafter; and zero otherwise[14]. γ tests how these announcements affect information share of the index futures prices.

Admati and Pfleiderer (1988), Bessembinder and Seguin (1993) and Martinez and Tse (2008) find that surprises in trading volume have different impacts on market volatility compared with expected changes. Therefore we are interested in examining the effects of expected and unexpected

[11] Note that we compute the conditional GIS series for the Shanghai Stock Exchange A share index and CSI 300 stock index futures and the one for the Shenzhen Stock Exchange A share index and CSI 300 stock index futures, respectively.
[12] Note that the futures market refers to the CSI 300 index futures market; the spot market refers to the Shanghai Stock Exchange A share index or the Shenzhen Stock Exchange A share index.
[13] Stationarity tests show that all the conditional GIS series are stationary. And all the explanatory variables are tested to be stationary. Test results are available upon request.
[14] According to Han and Liang (2017), the announcements include: (i) the initial margin for non-hedging trades would be raised to maximally 20%; (ii) any single day's total opening position greater than 600 contracts would be considered abnormal trade and subject to enhanced scrutiny; (iii) the clearing fees for intraday trades would be adjusted upward to 1.15 basis points.

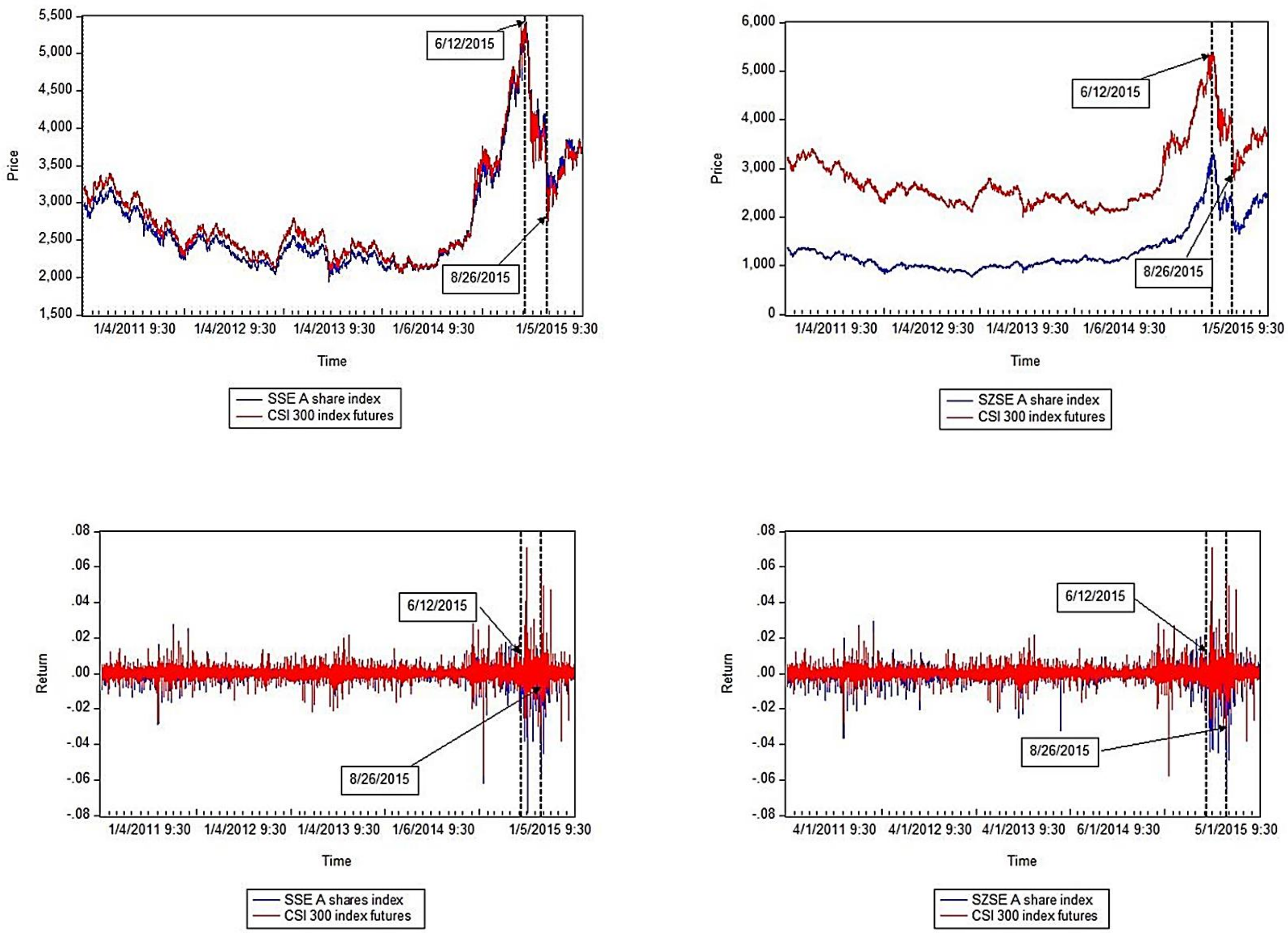
trading volume on information shares, respectively. $EV_{f,t}$ and $EV_{s,t}$ denote the expected trading volume of the futures and A share stock markets, respectively. $UnEV_{f,t}$ and $UnEV_{s,t}$ represent the unexpected trading volume of the futures and A share stock markets, respectively. β_1 tests whether trading volume expected by market participants contributes to information content of A-share index and index futures prices[15].

As proposed by Admati and Pfleiderer (1988) and Martinez and Tse (2008), the unexpected trading volume might reflect informed trading activities since it links to volatility. Given such relation, we include β_2 to test whether the unexpected trading volume directly contributes to information share.

Following Capelle-Blancard (2001), Chakravarty et al. (2004), Chen and Gau (2009, 2010), and Xu and Wan (2015) who suggest that volatility is an important factor for information share, we specify the relative volatility ($\sigma_{f,t}/\sigma_{s,t}$) of each pair of markets in question in Equation (11) to examine the volatility effects on information share. $\sigma_{f,t}$ and $\sigma_{s,t}$ are estimated standard deviations from the AG-DCC GARCH model for futures and spot markets, respectively. We also include the relative number of trades ($NoTrade_{f,t}/NoTrade_{s,t}$) of each pair of markets in Equation (11) to investigate its effect on information share as in Ates and Wang (2005)[16]. Note that both $\sigma_{f,t}/\sigma_{s,t}$ and $NoTrade_{f,t}/NoTrade_{s,t}$ are control variables in Equation (11).

[15] The derivation process for the expected and unexpected trading volume is shown in Appendix 3.
[16] A ratio of bid-ask spread between the index futures and A share stock markets is also included in Equation (11) (Ates and Wang, 2005; Chen and Gau, 2010; Xu and Wan, 2015). We find that its coefficient is always significant and negative for all the cases, consistent with the literature. Moreover, the results of the other coefficients in the model with that ratio are the similar to those without it. Hence we exclude the ratio of bid-ask spread in Equation (11) for the estimation process.

Figure 1. One-minute price and return movements



3. Data and Sample Statistics

We collect minute-by-minute prices of the Shanghai Stock Exchange (SSE) A share index, the Shenzhen Stock Exchange (SZSE) A share index, and the China Securities Index (CSI) 300 futures contracts. In addition, we obtain at 1-minute intervals, trading volume and the number of trades of the A share stocks in the Shanghai and Shenzhen stock exchanges as well as the stock index futures contracts. Note that we calculate the pairwise static and time-varying performance of price discovery between the SSE A share index and CSI 300 index futures and between the SZSE A share index and CSI 300 index futures, respectively. Data is obtained from Thomson Reuters Tick History (TRTH).

The sample period is from June 12, 2015 to August 26, 2015 during which the market crash occurred. The data series of CSI 300 index futures are obtained from the most nearby contracts which is are defined as the contract that has the nearest maturity date and normally expires within each calendar month. The most nearby contract is the most liquid in each calendar month, and is widely employed for the studies on futures markets in the literature (see, e.g. Chan et al., 1991; Chan, 1992; Koutmos and Tucker, 1996; Kim et al., 1999; Tse, 1999; Kavussanos et al., 2008; Bohl et al., 2011; Yang et al., 2012). To avoid biases caused by irrational trading behaviour when the maturity date approaches, we roll the contract over to the next five working days before the contract expires[17]. Spot and futures prices recorded before either the stock or futures exchange opens or after either of them closes are excluded from the sample. We end up with 12776

[17] The biases are referred to as the expiration-day effects in the literature. The effects result from an abnormal volatility of futures prices that occurs in the last weeks of life for futures contracts (Samuelson, 1965). If futures price records of this period are used for analysis, results concluded from statistical inferences could be distorted from the abnormal volatility (Carchano and Pardo, 2009). Ma et al. (1992) suggest that futures prices around the expiration date should be avoided, as they always have excessive volatility. Factors causing such effects are discussed in Stoll and Whaley (1997).

observations for pairs of data series of SSE A share index and CSI 300 index futures while 12651 observations for pairs of data series of SZSE A share index and CSI 300 index futures.

We employ Chow's breakpoint test to check whether there are structural breaks on those selected dates. The null hypothesis of no structural breaks is rejected, validating the splits of the original sample[18]. Original prices are taken in the form of natural logarithms and returns are calculated by taking the first difference of the logarithmic prices. Trading volume is also taken in the form of natural logarithms.

Table 1. Descriptive statistics of one-minute returns of SSE A share index, SZSE A share index, and CSI 300 index futures

	Nobs	*Mean*	*Std*	*Skew*	*Kurt*	*Max*	*Min*	*JB statistics*
Panel A: SSE A share & CSI 300 Futures								
SSE A	12776	-4.38×10^{-5}	0.0021	-6.5524	277.3123	0.0581	-0.0786	$4.01\times10^{7***}$
CSI 300	12776	-5.07×10^{-5}	0.0029	1.2086	46.6867	0.0708	-0.0381	$1.02\times10^{6***}$
Panel B: SZSE A share & CSI 300 Futures								
SZSE A	12651	-4.78×10^{-5}	0.0021	-6.9387	214.8447	0.0469	-0.0654	$2.38\times10^{7***}$
CSI 300	12651	-5.12×10^{-5}	0.0029	1.2037	46.3165	0.0708	-0.0381	$9.92\times10^{5***}$

Notes: This table reports the descriptive statistics of 1-minute returns of SSE A share index, SZSE A share index, and CSI 300 index futures. Note that there are two samples under investigation in this study. The first sample contains pairs of data series of SSE A share index and CSI 300 index futures while the second one contains pairs of data series of SZSE A share index and CSI 300 index futures. The sample period is equally from June 12, 2015 to August 26, 2015. *SSE A share* denotes the Shanghai Stock Exchange A share index. *SZSE A share* denotes the Shenzhen Stock Exchange A share index. *CSI 300* denotes the CSI 300 index futures. *Nobs* denotes the number of observations; *Mean* denotes mean of sample; *Std* denotes standard deviation; *Skew* denotes skewness; *Kurt* denotes kurtosis; *Max* denotes maximum value; *Min* denotes minimum value; *JB statistics* denotes statistics of the Jarque-Bera test for normality. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Figure 1 depicts the movements of original prices and logarithmic returns before, during and after the market crash. We mark the start and end points of time for the market crash in the figure. It can be clearly observed in the figure that prices (returns) of both the SSE and SZSE A share indices move in tandem with prices (returns) of the CSI 300 index futures across time. This

[18] Results of test statistics are available upon request.

indicates the possibility of a strong linkage between prices of indices and index futures. Figure 1 also shows that prices and returns during the crisis period behave differently compared with the rest of the sample period, with sharp drops in both indices and index futures prices during the crisis. Meanwhile, the deviations of returns from their central values in the crisis period seem larger than those in the other periods.

Table 2. Unit-root tests on futures and index prices

	Logarithm of Index Price					*Logarithm of Futures Price*			
	Level		*First Difference*			*Level*		*First Difference*	
	ADF	*PP*	*ADF*	*PP*		*ADF*	*PP*	*ADF*	*PP*
SSE A share					*CSI 300*				
	-0.808	-0.817	-43.190***	-81.581***		-0.568	-0.575	-30.231***	-111.994***
SZSE A share					*CSI 300*				
	-1.178	-1.168	-41.389***	-79.621***		-0.582	-0.569	-28.595***	-112.312***

Notes: This table shows the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit-Root Tests on the natural logarithm of prices of the SSE A share index, SZSE A share index, and CSI 300 index futures. The results on the original level and the first difference of price series are reported, respectively. The first difference is calculated by prices at time *t* less prices at time *t*-1. *SSE A share* denotes the Shanghai Stock Exchange A share index. *SZSE A share* denotes the Shenzhen Stock Exchange A share index. *CSI 300* denotes the CSI 300 index futures. *ADF* denotes the Augmented Dickey-Fuller unit-root test and *PP* denotes the Phillips-Perron unit root test. ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

Table 1 summarises the descriptive statistics of returns of the two indices as well as the index futures. We note the following observations from Table 1. First, the crisis period evidently shows negative mean returns which is not surprising as Figure 1 shows large price drops during the crash period. Second, the crash period has a large standard deviation. This is again, unsurprising as markets are expected to be volatile during the crash. Meanwhile, Table 1 also shows that the index futures market is more volatile than the stock markets during the crash. Third, the values of skewness and kurtosis are large with both the SSE and SZSE A share index returns negatively skewed whereas returns of the CSI 300 index futures are positively skewed. The returns of equity indices are more skewed than those of the index futures. Excess kurtosis is evident in both equity index and index futures returns. The distributions of all the returns are fat-tailed. The Jarque-Bera test suggests that returns of the two indices and index futures do not follow a normal distribution. We take account of this non-normality in the estimation of the AG-DCC GARCH model.

Table 2 presents the results of the Augmented Dickey-Fuller (Dickey & Fuller, 1979) and Phillips-Perron (Phillips & Perron, 1988) tests. Results clearly show that the index and futures prices have a unit root. In contrast, their returns are stationary[19]. Since the index and futures prices are integrated at the same order (at order 1), pairs of series may be cointegrated.

Table 3. Johansen cointegration tests

	Cointegrating Vector		*Zero Cointegrating Vector (r = 0)*		*One Cointegrating Vector (r = 1)*		*Restrictions on Cointegrating Vector*
	Coeff. of S_t	*Coeff. of F_t*	λ_{max}	*Trace*	λ_{max}	*Trace*	*Likelihood –ratio test statistic*
SSE A share & CSI 300							
	1	-0.889	24.808***	28.495***	3.687	3.687	11.137***
SZSE A share & CSI 300							
	1	-0.933	12.550**	14.436**	1.886	1.886	8.180***

Notes: This table shows the results of the Johansen cointegration tests on prices of the SSE A share index, SZSE A share index, and the CSI 300 index futures. *SSE A share* denotes the Shanghai Stock Exchange A share index. *SZSE A share* denotes the Shenzhen Stock Exchange A share index. *CSI 300* denotes the CSI 300 index futures. *Coeff.* stands for coefficient. S_t denotes index prices while F_t denotes index futures prices. λ_{max} is the max-eigenvalue test statistic. *Trace* denotes the trace test statistic. *r* refers to the number of cointegrating vector. The likelihood ratio test is conducted on restricting the cointegrating vector to be (1,-1). ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

[19] The unit-root tests are also performed on the logarithms of trading volume and number of trades of two indices and index futures. The results suggest that they are all stationary during the market crash. The results are available upon request.

The Johansen (1991) cointegration tests on the paired series between the stock indices and index futures are reported in Table 3[20]. Both the Trace and λ-Max statistics indicate that prices of the SSE and SZSE A share index are cointegrated with the CSI 300 index futures prices. Moreover, the likelihood ratio tests are performed to examine whether the vector of the cointegrating coefficients can be held to be (1,-1). The null hypotheses are all rejected, suggesting the restrictions on the cointegrating coefficients cannot hold. This validates the use of GIS[21].

4. Empirical Results

4.1. Static and time-varying GIS

Results of the unconditional GIS measure are summarised in Table 4. The GIS of the Shanghai market is lower than that of the index futures market. Price discovery takes place mostly in the index futures market, suggesting that it leads the Shanghai market during the crisis. A similar result is obtained for the Shenzhen share market that the index futures market leads the spot market in the long run during the crisis period as evidenced by higher GIS of the former. Overall, Table 4 suggests that the CSI 300 index futures market performs as expected in terms of price discovery.

[20] When performing the cointegration tests, we choose the testing model with no intercept and deterministic trend in the cointegrating vector and no intercept and deterministic trend in the test Vector Autoregressive (VAR). The optimal lags in the VAR are selected based upon the AIC criterion.
[21] It should be noted that the likelihood ratio test does not reject the inclusion of intercept; however, the one-to-one cointegrating relation is rejected.

Table 4. Constant GIS Measure

	SSE	*CSI*
GIS	0.202	0.798
	SZSE	*CSI*
GIS	0.294	0.706

Notes: This table reports the static estimates of GIS measure. *SSE* denotes the Shanghai stock exchange A share index; *SZSE* denotes the Shenzhen stock exchange A share index; and *CSI* denotes the CSI 300 index futures. *GIS*, Generalized Information Share.

To obtain estimates of the conditional GIS, the bivariate AG-DCC GARCH model is estimated first. The estimation results are shown in Table 5. The model is well specified given that none of the Ljung-Box Q statistics for standardised residuals and their squares are significant at any conventional level. This indicates that there are no autocorrelation and heteroscedasticity in the standardised innovations.

Table 5. AG-DCC GARCH Model

Coeff.	*SSE* (i = 1)	*CSI* (i = 2)	*SZSA* (i = 1)	*CSI* (i = 2)
α_{1i}	-0.615*** (0.0319)	-0.196*** (0.0074)	-1.291*** (0.0021)	-0.201*** (0.0014)
α_{2i}	0.157*** (0.0187)	0.132* (0.0771)	0.200*** (0.0045)	0.137*** (0.0186)
α_{3i}	-0.006 (0.0229)	-0.004 (0.1160)	-4.92×10^{-5} (0.0002)	-0.004 (0.0291)
α_{4i}	0.944*** (0.0030)	0.975*** (0.0011)	0.906*** (3.54×10^{-5})	0.989*** (3.87×10^{-5})
a_{ii}	0.200* (0.1104)	-0.350*** (0.0372)	0.200*** (0.0746)	0.210 (0.3198)
b_{ii}	0.656*** (0.0524)	0.865*** (0.0167)	0.449*** (0.0881)	0.586** (0.2450)
g_{ii}	0.050 (0.0481)	0.050 (0.0697)	0.047 (0.1598)	0.050 (0.2430)
ξ_i	0.971*** (0.0174)	7.221*** (0.1746)	0.840*** (0.0092)	10.940*** (0.1347)

v	2.869^{***} (0.0363)		2.256^{***} (0.0049)	
LB(12)	6.286	3.404	16.070	5.684
LB²(12)	1.847	9.412	0.143	2.872

Notes: This table reports the estimation results of the bivariate AG-DCC GARCH model. Note that the coefficients of Equations (9), (10) & (A2.1) are estimated and reported. *SSE* denotes the Shanghai stock exchange A share index; *SZSE* denotes the Shenzhen Stock Exchange A share index; and *CSI* denotes the CSI 300 index future. *LB(12)* and *LB²(12)* are the Ljung-Box Q statistics at order 12 for the standardized residuals and their squares, respectively. *Coeff.* stands for coefficients. Figures in the parentheses are standard errors. ***, **, and * indicate significance at the 1, 5, and 10%, respectively.

The conditional heteroscedasticity in returns is well addressed as evidenced by significant α_{2i} and α_{4i}. Volatility is not only affected by arrival of new information (new shocks) but is also explained by old information (persistence). This is evident for the two A share indices and index futures. We find no evidence of volatility asymmetry in the A share index and index futures. The finding does not agree with Wen et al. (2011) and Hou and Li (2015) who find asymmetry of volatilities at larger time intervals during tranquil periods. This implies that investors in the Chinese stock and stock index futures markets are insensitive to bad news arising in the past at very short time windows. One could reasonably attribute such response from those investors in the futures market to stringent monitoring of futures transactions by local market regulators. As to the A share markets, a possible reason could be the inability of investors to respond to bad news at fairly short intervals since bad news cluster more intensively in a market crash than in normal periods in terms of arrival speed and amount. Lastly, all the kurtosis and skewness coefficients are statistically significant. This indicates that the non-normality of returns are well accounted for by the model.

We also find that the correlations between the two A share indices and index futures are persistent over time. However, there is no evidence that the correlations are heightened when both markets are bearish. One reasonably expects such result since all the markets are bear markets at most points in time during the market crash and there are very few observations of positive returns.

Thus it might be hard to identify the difference between the effects of past negative and positive shocks on correlation.

Table 6. Descriptive Statistics of Conditional GIS Measure

	Mean	***Std***	***Max***	***Min***
SSE	0.105	0.042	0.350	2.07×10^{-6}
CSI	0.895	0.042	1.000	0.650
SZSE	0.034	0.009	0.452	4.40×10^{-4}
CSI	0.966	0.009	1.000	0.548

Notes: This table reports the descriptive statistics of estimates of the conditional GIS measure based upon the AG-DCC GARCH model. *SSE* denotes the Shanghai stock exchange A share index; *SZSE* denotes the Shenzhen Stock Exchange A share index; and *CSI* denotes the CSI 300 index futures. *Mean* denotes mean of sample; *Std* denotes standard deviation; *Skew* denotes skewness; *Kurt* denotes kurtosis; *Max* denotes maximum value; *Min* denotes minimum value.

The descriptive statistics of the estimated conditional GIS is reported in Table 6. The mean GIS of the Shanghai market is smaller than that of the index futures during the market crisis, indicating that the futures market plays a leading role in the crisis period. The conditional GIS measures are consistent with the static ones reported earlier in Table 4 but provide more affirmative results. The standard deviations of the GIS series of these two markets are small, suggesting that the estimates are stable over time. On the other hand, the CSI 300 index futures market has a higher mean than the Shenzhen share market, suggesting that the index futures market dominates the price discovery process. This result confirms what is reported in Table 4 but is much more significant. Also, the GIS series of these two markets are stable given their small standard deviations. Our results highlight the importance of accounting for time variation in information shares[22].

In sum, both static and conditional GIS measures indicate that the CSI 300 index futures market leads in the price discovery process, as expected, relative to the Shanghai and Shenzhen

[22] The unit-root tests are conducted on the conditional GIS series. Test results indicate that all the obtained series are stationary. These results are available upon request.

share markets during the recent market crash[23]. This finding aligns with Chen et al. (2013), Guo et al. (2013), Hou and Li (2013, 2015) and Xu and Wan (2015) who report that the CSI 300 index futures benefits the Chinese stock markets in tranquil periods. The behaviour of the Chinese index futures market in light of its functionality toward the underlying stock markets during the market crash is similar to Harris (1989) on the S&P 500 market and Cheng et al. (2000) on the Hong Kong market.

4.2. Effects of trading volume components and regulatory intervention

The effects of market variables on the relative GIS of the index futures market are shown in Table 7. We use Newey and West (1987) robust standard errors to cope with autocorrelation and heteroscedasticity in the residuals.

Table 7. Regression Model on Conditional GIS

Coeff.	*CSI/SSE*		*CSI/SZSE*	
β_0	-260.926**	(124.3539)	21.643***	(3.1153)
γ	-121.660*	(69.4826)	-0.431	(0.7711)
β_1	657.814**	(303.935)	12.835***	(4.3291)
β_2	8.20×10^{-5}	(0.0017)	-5.26×10^{-5}	(6.40×10^{-5})
β_3	3.315	(2.5111)	7.78×10^{-6}***	(3.37×10^{-6})
β_4	-15.090**	(6.8557)	-0.143***	(0.0444)
Log-likelihood	-126383		-60480	

Notes: This table reports the estimation results of Equation (11). γ, the coefficient for the announcement dummy; β_1, the coefficient for the logarithmic ratio of the size of expected trading volume; β_2, the coefficient for the logarithmic ratio of the size of unexpected trading volume; β_3, the coefficient for the logarithmic ratio of volatility; β_4, the coefficient for the logarithmic ratio of number of trades. The ratios are between A share and index futures markets. *SSE* denotes the Shanghai stock exchange A share index; *SZSE* denotes the Shenzhen Stock Exchange A share index; and *CSI* denotes the CSI 300 index futures. *CSI/SSE* denotes the dependent variable of the equation that is the natural logarithm of the ratio between the GIS of the CSI 300 index futures and Shanghai Stock Exchange A share index. *CSI/SZSE* denotes the dependent variable of the equation that

[23] The conditional GIS measure estimates of the SSE A share index, SZSE A share index and CSI 300 index futures are calculated based upon a trivariate VECM AGDCC-GARCH model (Y_t is a 3×1 vector in Equation (2)). The results are shown in Table A5.1 in Appendix 5. Note that Table A5.1 is consistent with Table 6.

is the natural logarithm of the ratio between the GIS of the CSI 300 index futures and Shenzhen Stock Exchange A share index. *Coeff.* stands for coefficients. Figures in the parentheses are the Newey-West robust standard errors. ***, **, and * indicate significance at 1, 5 and 10% levels, respectively.

It is evident from Table 7 that the price discovery process from the index futures to the Shanghai market is substantially impeded by a series of announcements made on August 25, 2015 to curb the speculative futures trading, given the statistically significant and negative γ. The information content of both Shanghai A share index and index futures prices appears to be impaired by the harsh measures that almost terminated futures trading (Han and Liang, 2017). This result is consistent with Han and Liang (2017) who find those announcements lead to the deteriorating quality of information content in the CSI 300 and 500 spot markets in China.

We also find that the leading role the futures market plays relative to the Shenzhen market is impaired but rather weak after August 25 since γ is negative but not significant. Hence there is no significant difference in the price discovery function of the index futures market relative to the Shenzhen market before and after the announcements. One possible reason for this is the relatively low sensitivity of Chinese retail investors to changes in the index futures market. This low sensitivity may be due to stringent trading regulations that constrain them from futures trading[24]. Since activities of retail investors cluster more intensively in Shenzhen than in Shanghai[25], one could argue that the halted futures trading may have a weaker impact on the informational effect of the index futures market on the Shenzhen market.

The coefficient of the relative expected trading volume (β_1) is positive and statistically significant. While the expected trading volume of the index futures contracts grows faster than that of both Shanghai and Shenzhen share markets, the information share of the former increases. This result suggests that the expected trading volume contributes to information content in either

[24] See details on these constraints in Appendix 1.
[25] Please see discussions on this in Appendix 4.

market during the crash; thus it reflects informed trading activities. This confirms the importance of trading activities by major market participants in the crisis event. In a sense, this finding aligns with Han and Liang (2017) who find that the forced termination of index futures trading deteriorates the quality of information of the stock markets in China during the same event.

We find no evidence that the unexpected trading volume increases GIS. Trading volume shocks have little impact on the information content of either index or futures prices, and thus fail to detect informed trading activities. The result is different from Martinez and Tse (2008), implying that the informational linkage between volume shocks and information content of prices in an abnormal period is not as strong as that in a normal one.

Turning to our control variables, volatility reinforces the information share of the futures market relative to the Shenzhen share market, it being a proxy for the rate of arrival of information even during the crash. The finding is consistent with the literature (Capelle-Blancard, 2001; Chakravarty et al., 2004; Chen and Gau, 2009, 2010; and Xu and Wan, 2015). When the number of trades per minute in the index futures market grows faster than in either Shanghai or Shenzhen A share market, less price discovery will take place in the former market. The adverse impact from speed of order execution implies operational inefficiency of the local trading system during the crash. This finding somewhat reflects some critiques on the local trading system of futures contracts that it provides so many opportunities for market speculators to put a trigger on huge price drops during the early days of the crash[26].

[26] The CSI 300 index lost over 34% in 20 days, with 1000 points erased in 1 week alone.

5. Concluding Remarks

Although pricing dynamics of the stock index futures market during market crashes are explored in the literature, conclusions on its informational role remain controversial. By employing the recently developed generalised information share (GIS) and its time-varying transformation, we explore the price discovery process in the Chinese index futures market during a recent market crash. We examine the effect of government intervention and different components of trading volume on information shares of the spot and futures markets. We employ a bivariate VEC AGDCC-GARCH model to estimate static and time-varying GIS of the index futures market and the Shanghai and Shenzhen A share markets in China.

The conditional GIS of the SSE A share index and CSI 300 index futures agrees with its static measure in that the index futures market plays a leading role in price discovery during the crisis period. On the other hand, both static and time-varying GIS indicate that the index futures market leads in price discovery as expected, with respect to the Shenzhen A share market. The results drawn from the conditional GIS are more significant, which underscores the importance of accounting for time-varying transformation. Therefore, the Chinese stock index futures market leads both the Shanghai and Shenzhen A share markets during the crisis in the long run. This finding supports the argument in the literature that the performance of the stock index futures market is retained during a market crash.

We find that a series of announcements made to freeze the index futures trading during the market crash adversely impact information content of both the A share indices and index futures prices. Such effect is evident in the price discovery process between the index futures and the Shanghai share markets. The downgraded informational role of A share markets as a result of those harsh measures is consistent with the deteriorating effects on the CSI 300 and 500 spot markets found by Han and Liang (2017).

The effects of trading volume components on the GIS of the CSI 300 stock index futures relative to both the Shanghai and Shenzhen A share markets are significant. We find that the expected trading volume is a major driver of the information share of the index futures market. This result implies that trading activities of the major market participants may help to increase market efficiency during a market crash, unlike government interventions to limit the trading activities which tend to impair market efficiency. In contrast, unlike in normal periods, volume shocks during a market shock is not a good proxy of informed trading activities.

Appendix 1 Characteristics of the Chinese stock index futures markets

The Chinese stock market contains two types of securities that are available to trade. One type is called 'A shares' and the other is called 'B shares'. Domestic investors in China can trade both A share and B share stocks while foreign qualified investors are only allowed to trade B share stocks. A share and B share stocks are both traded in the Shanghai and Shenzhen stock exchanges.

The Chinese stock index futures contract with the China Securities Index (CSI) 300 index as the underlying spot asset was introduced on April 16th 2010. It is the first index futures contract for A share stock market in China and is strictly monitored by the regulators. For example, to open an account for stock index futures trading, a deposit of RMB 500,000 is required for domestic retail investors and RMB 1 million is required for market participants. The domestic retail investors must pass the qualification exam. Trading index futures contracts is recommended for individual investors as explicitly mentioned in related regulatory documents issued by China Securities Regulatory Commission (CSRC) (Yang et al., 2012). The initial margin requirement is relatively high as it is 15% for the current and next month contracts and 18% for the next two quarter-month contracts. The Qualified Foreign Institution Investors (QFIIs) are allowed to trade the CSI index futures for hedging purpose only.

The trading venue of the CSI 300 index futures is the China Financial Futures Exchange (CFFEX). Maturity months of the CSI 300 index futures contracts traded in each calendar month include the current month, the next month, and the two nearest quarter-end months (i.e., March, June, September, and December). For instance, futures contracts traded in the calendar month of May include contracts expiring in May, June, September and December. The contract multiplier is RMB 300. The maturity date is the third Friday of the maturity month. On the maturity date, the index futures contracts are cash settled. Day trading of the CSI 300 index futures contracts is from 9:15 a.m. to 11:30 a.m. and from 1:00 p.m. to 3:15 p.m. Beijing Time. In comparison, trading hours of the Shanghai and Shenzhen stock exchanges on a business day are from 9:30 a.m. to 11:30 a.m. and from 1:00 p.m. to 3:00 p.m.

The stock index futures market differs from the local stock markets in terms of the following. Most of the listed stocks in the Shanghai and Shenzhen stock exchanges are issued by state-owned enterprises (SOEs) in China. The proportion of their shares that are tradable is relatively small and thus the security supplies are scarce. As a result, the market is vulnerable to speculation. However, the stock index futures contracts are supplied by CFFEX, suggesting that there are sufficient supplies of the index futures contract. In the Chinese A share markets, a $T + 1$ trading mechanism is maintained by the market regulators. Investors who purchase stocks today are not allowed to trade them until the next trading day, which precludes the opportunities of intraday trading. In contrast, a $T + 0$ trading mechanism operates within the stock index futures market where intraday trading of futures contracts is available. Besides, investors are freer to do short selling in the stock index futures market than the A share markets. Last, retail investors dominate the A share markets whereas institutional investors occupy the index futures market in China (Ng and Wu, 2007; Yang et al., 2012).

Appendix 2 Maximum likelihood estimation (MLE) of a bivariate AGDCC GARCH model

Parameter estimates in the AG-DCC model are obtained through maximizing the log-likelihood of the probability density function (PDF) of innovations ε_t. ε_t is proposed to follow a bivariate skewed Student's *t* distribution that accounts for both excess kurtosis and skewness. Excess kurtosis, which corresponds with fat tails of distribution, is widely observed in financial time series (Bollerslev, 1987; Baillie and Bollerslev, 1989). In addition, the unconditional distribution of financial returns is often skewed so that capturing the skewness for the conditional distribution is needed (Park and Jei, 2010). Accepting only conditional normality in the estimation of the multivariate GARCH models for non-normal data could result in loss of efficiency (Engle and Gonzalez-Rivera, 1991; Park and Jei, 2010). Thus the utilization of the conditional distribution that captures both excess kurtosis and skewness for the estimation of the multivariate GARCH models could yield more reliable results in cases where the underlying data deviates from normality (Susmel and Engle, 1994; Tse, 1999; Bauwens and Laurents, 2005).

We employ Bauwens and Laurents (2005)'s multivariate skewed Student's *t* density for the standardized innovations ϵ_t, which is based upon Fernandez and Steel (1998)'s skewed filter to multivariate Student's *t*. The contribution of each observation at time *t* to the log-likelihood of a standardized bivariate skewed-*t* can be expressed in general term as

$$l_t(\Theta) = \log(\tfrac{4}{\pi}) + \textstyle\sum_{i=1}^{2} \log(\tfrac{\xi_i s_i}{1+\xi_i^2}) + \log\left\{\Gamma\left(\tfrac{v+2}{2}\right)/(\Gamma\left(\tfrac{v}{2}\right)(v-2))\right\} - (1/2)\,(v+2)\log[1 + (\kappa_t^T \kappa_t)/(v-2)]. \qquad \text{(A2.1)}$$

where

$$\kappa_t = (\kappa_{1t}, \kappa_{2t})^T$$

$$\kappa_{it} = (s_i \epsilon_{it}^* + m_i)\xi_i^{-I_i}$$

$$m_i = \frac{\Gamma\left(\frac{v-1}{2}\right)\sqrt{v-2}}{\sqrt{\pi}\,\Gamma\left(\frac{v}{2}\right)}(\xi_i - \frac{1}{\xi_i})$$

$$s_i^2 = \left(\xi_i^2 + \frac{1}{\xi_i^2} - 1\right) - m_i^2$$

$$I_i = \begin{cases} 1 & \text{if } \epsilon_{it}^* \geq -\frac{m_i}{s_i} \\ -1 & \text{if } \epsilon_{it}^* < -\frac{m_i}{s_i} \end{cases}.$$

Note that Γ is the gamma function and *v* is the degree of freedom for bivariate Student's *t*. *v* is restricted to be more than 2 so that the covariance matrix can exist. *v* governs the thickness of tails of the distribution, that is, the kurtosis. $m_i(\xi_i, v)$ and $s_i(\xi_i, v)$ are the mean and standard deviation of the non-standardized marginal skewed-t of Fernandez and Steel (1998). ξ_i is the skewness parameter where the sign of the logarithm of ξ_i indicates the direction of the skewness. When $ln\xi_i > 0$ (< 0), the skewness is positive (negative) and density is skewed to the right (left). The covariance matrix of ϵ_{it}^* is an identity matrix.

Θ is a parameter vector with all of the coefficients of the AG-DCC GARCH model. Estimates for parameter vector Θ can be obtained by maximizing Equation (A2.1) over the sample period, which is expressed as

$$L(\Theta) = \sum_{t=1}^{T} l_t(\Theta). \qquad \text{(A2.2)}$$

where T is the sample size.

Appendix 3 Derivation of expected and unexpected trading volume

Similar to Martinez and Tse (2008), the expected and unexpected trading volume are obtained through three steps. First, stationary series of collected trading volume are specified in an ARMA (10, 0) model[27]. Then the one-step-ahead forecast error is calculated for each volume series as follows:

$$\hat{\zeta}_{it} = Volume_{it} - E[Volume_{it} | Volume_{i,t-\tau}, \tau = 1, \ldots, 10]. \quad \text{(A3.1)}$$

where $i = s, f$. f denotes futures market while s denotes spot market[28]. ζ_{it} is the one-step-ahead forecast error. $Volume_{it}$ denotes the actual values of volume. And $E[Volume_{it} | Volume_{i,t-\tau}, \tau = 1, \ldots, 10]$ represents the estimated volume values from the proposed ARMA model.

Second, the unexpected component of trading volume ($UnEV_{i,t}$) is obtained by regressing $\hat{\zeta}_{it}$ on lagged values of volatility and volume. The volatility is the fitted standard deviation from the AG-DCC GARCH model. The regression model is

$$\hat{\zeta}_{it} = \varphi + \sum_{j=1}^{10} \gamma_{ij} \hat{\sigma}_{it-j} + \sum_{k=1}^{10} \delta_{ik} Volume_{it-k} + v_{it}. \quad \text{(A3.2)}$$

where $\hat{\sigma}_{it-j}$ is the estimated lagged standard deviations. $Volume_{it-k}$ denotes the lagged values of trading volume. The unexpected trading volume is the estimated residuals $\hat{v}_{it}$. Thus we have $UnEV_{i,t} = \hat{v}_{it}$.

Third, the expected volume ($EV_{i,t}$) is obtained by subtracting the unexpected component from the original volume series:

$$EV_{i,t} = Volume_{it} - \hat{v}_{it}. \quad \text{(A3.3)}$$

[27] Results of unit root tests are available upon request.
[28] Spot market refers to the SSE A share market or the SZSE A share market.

Appendix 4 A Comparison between the Shanghai and Shenzhen stock exchanges

The Shanghai and Shenzhen A share markets differ in terms of scale, liquidity, and composition of investors. The Shanghai stock exchange has more publicly listed companies that issue A-share stocks than the Shenzhen stock exchange. Since most issuing companies are State-Owned Enterprises (SOEs), the supply of tradable shares in Shanghai is much higher than that in Shenzhen. Thus, the larger Shanghai A share market could reasonably be expected to attract more participants and more informed traders than Shenzhen.

The Shanghai market is also expected to have higher liquidity than Shenzhen given its higher supply of tradable shares. In addition, the mean trading volume in Shanghai is larger than in Shenzhen. At the same time, the mean of the number of trades in Shanghai is lower than in Shenzhen[29]. Thus the average volume of each trade in Shanghai is higher than in Shenzhen which underscores the fact that the Shanghai market is more liquid than Shenzhen.

Furthermore, the average volume per trade has implications on the composition of investors. In the literature, institutional investors are perceived to be well endowed and highly skilled in executing trades (Ng and Wu, 2007; Bohl et al, 2011; Xu and Wan, 2015). With a large amount of wealth, resources and superior channels to obtain information, one could intuitively expect that institutional investors execute more buy or sell orders in one trade than the retail investors in order to swiftly ride on private information they possess. Thus, a high average volume per trade implies a high proportion of institutional investors. Hence, given the higher average volume per trade in the Shanghai A share market, it may have more active institutional investors than Shenzhen. Conversely, the relatively low average volume per trade in Shenzhen may signal that the proportion of retail investors in that market may be high.

[29] Test statistics are available upon request.

Appendix 5 Time-varying GIS of the SSE A share index, SZSE A share index, and CSI 300 index futures in a trivariate VECM AGDCC-GARCH model

Table A5.1 Descriptive statistics of conditional GIS measure

	Mean	*Std*	*Max*	*Min*
SSE	0.102	0.041	0.350	1.981×10^{-6}
CSI	0.868	0.040	0.996	0.451
SZSE	0.030	0.008	0.372	4.268×10^{-4}

Notes: This table reports the descriptive statistics of the conditional GIS measure based upon a trivariate VECM AG-DCC GARCH model. *SSE* denotes the Shanghai stock exchange A share index; *SZSE* denotes the Shenzhen Stock Exchange A share index; and *CSI* denotes the CSI 300 index futures *Mean* denotes mean of sample; *Std* denotes standard deviation; *Max* denotes maximum value; *Min* denotes minimum value.

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