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Volatility Spillovers in China's Financial Markets During the 2015 Stock Market Crash: Evidence From DCC-GARCH and the DY Approach

Fangning Gan

University of International Business and Economics, Beijing, China
gancao1126@163.com

Abstract. This paper examines volatility spillovers among the stock, foreign exchange, money, and bond markets of China during the 2015 stock market crash. Using daily series of the CSI 300 index, the USD/CNY central parity rate, the 7-day Shanghai Interbank Offered Rate, and the 10-year Chinese government bond yield from the Wind Financial Database over January 2014 to December 2016, conditional volatilities are extracted with univariate sGARCH(1,1) models, the dynamic correlations of returns and interest rate changes are captured by the DCC-GARCH model, and the directional predictive contributions among conditional volatilities are measured by the generalized Diebold-Yilmaz (DY) spillover index. To address stationarity concerns, the reported statistics rely only on rolling windows with a stable vector autoregression. In crisis-stable windows the stock market is a net receiver of volatility spillovers, whereas the exchange rate and the long-term interest rate are net senders, with average predictive contributions of 5.948 and 2.795 percentage points to stock volatility. The average total connectedness index during the crisis under a 200-day window is 4.260%, lower than 7.420% before the crisis, while shorter windows reverse this comparison, indicating that phase comparisons depend on the time scale. Descriptive event-window comparisons show consistent directional changes in dynamic correlations around the crash onset and increases in the within-window mean of the total connectedness index after the exchange rate reform; these comparisons are descriptive and are not formally tested. The results document directional and phase-specific differences in volatility spillovers; interpretation is bounded by stationarity and rolling-window diagnostics.

Keywords: 2015 stock market crash, volatility spillover, conditional volatility, DCC-GARCH, DY spillover index

1. Introduction

The sharp stock market correction that started in June 2015 intertwined in time with the subsequent reform of the central parity quotation and with monetary policy operations, so that the volatility linkages among the stock, foreign exchange, money, and bond markets became central to understanding how financial markets functioned in that period. This paper addresses three research questions: first, how returns and interest rate changes across the four markets moved together around

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the onset of the crash; second, which markets provided more predictive information about the volatility of other markets; and third, when and over which time scale these volatility linkages changed.

Answering these questions is practically relevant. The year 2015 was a period of intensified financial market volatility and of dense macroeconomic and market policy announcements in China, and cross-market volatility spillovers bear directly on the choice of risk monitoring indicators and on the evaluation of stabilization policies. Identifying the role of each market in volatility transmission during the crisis provides empirical reference for asset allocation and for cross-market risk monitoring by regulators.

In terms of content, this paper takes daily data on the four markets from January 2014 to December 2016 as the sample, first describing the time-series features of conditional volatilities and the pairwise dynamic correlations, then measuring the directional predictive contributions among conditional volatilities, and finally conducting alternative specification checks and descriptive event-window comparisons. Methodologically, a two-step framework is adopted: in the first step, conditional volatilities are extracted with sGARCH(1,1) models and time-varying correlations of returns and interest rate changes are characterized by DCC-GARCH; in the second step, the directional predictive contributions among the four conditional volatility series are measured with the generalized DY spillover index, and their evolution over time is examined through rolling windows.

The remainder of the paper is organized as follows. Section 2 reviews the related literature, Section 3 describes the data sources and variable definitions, Section 4 presents the model specification and diagnostics, Section 5 reports the empirical results, Section 6 provides robustness checks and descriptive event-window comparisons, and Section 7 concludes.

2. Literature review

Research on risk and volatility transmission in Chinese markets has developed along several lines. Ahmed and Huo [1] examine how the 2015 stock market adjustment affected volatility linkages and information transmission between China and Asia-Pacific markets. Li et al. [2] study the asymmetry of risk spillovers among the Chinese stock, bond, money, and foreign exchange markets based on the GJR-BEKK-GARCH model and spillover index methods. Wang et al. [3] identify the net senders and net recipients of volatility in Chinese financial markets using variance decomposition networks. These studies generally find significant volatility co-movement among Chinese financial markets, with spillover intensity that is time-varying and asymmetric.

Methodologically, the measurement of volatility spillovers has long faced two difficulties, namely heteroscedasticity and variable ordering. Forbes and Rigobon [4] show that the rise in variance during crises inflates estimates of cross-market correlation and therefore requires correction. Univariate GARCH-type models provide the foundation for modelling time-varying volatility [5, 6], and their multivariate extensions evolved from constant conditional correlation [7] to dynamic conditional correlation, where the DCC model proposed by Engle [8] is more parsimonious in parameters; Bauwens et al. [9] provide a systematic survey of multivariate GARCH models. For spillover measurement, the generalized impulse response functions of Koop et al. [10] and Pesaran and Shin [11] avoid reliance on variable ordering, on which basis Diebold and Yilmaz [12, 13] construct spillover indices from generalized forecast error variance decompositions and extend them to directional and network-based analyses.

The volatility spillover examined in this paper refers to the generalized forecast error variance decomposition shares among GARCH conditional standard deviation series. It measures the

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predictive contribution of one market's volatility to the future volatility of another market and is a statistical association within the model, which cannot be equated directly with risk contagion in a causal sense. Compared with existing studies, this paper feeds the GARCH conditional volatilities of four domestic markets into the DY framework and reports variable definitions, parameter estimates, window settings, and stationarity diagnostics in a unified way, while explicitly distinguishing in-sample predictive contributions from real-time early warning capability.

3. Data sources and variable definitions

All four series are daily data from the Wind Financial Database, covering 2 January 2014 to 30 December 2016, with 733 common observations. After checking duplicates and missing values in ascending date order, transformations follow the definitions in Table 1, yielding an analytical sample of 732 observations from 3 January 2014: log returns are used for the stock index and the exchange rate, and first differences in basis points are used for the two interest rates. The full names, sources, raw series, and transformations of the variables are reported in Table 1.

Table 1. Data sources and raw series definitions

Variable and full name	Source	Raw series and unit	Transformation entering GARCH
CSI300 (CSI 300 index)	Wind	Daily closing index level (points)	100 x log difference (%)
USDCNY (USD/CNY central parity rate)	Wind	Daily central parity (CNY per USD)	100 x log difference (%)
SHIBOR7D (7-day Shanghai Interbank Offered Rate)	Wind	Daily quoted rate (%)	100 x first difference (basis points)
BOND10Y (10-year Chinese government bond yield)	Wind	Daily yield level (%)	100 x first difference (basis points)

Note: The 733 raw USDCNY observations match the RMB central parity rate published by the State Administration of Foreign Exchange day by day (see footnote); the specific curve name and Wind field code of the bond yield were not retained with the original attachments and still require verification against the original export metadata.

USDCNY is quoted in CNY per USD, so an increase indicates depreciation of the renminbi; a positive correlation between its return and the stock return indicates co-movement in the same direction, whereas a negative correlation indicates co-movement in opposite directions. SHIBOR measures the price of short-term funding, and the government bond yield measures the long-term interest rate level; a rise in the bond yield generally corresponds to a fall in the bond price, while the price return of a bond also involves duration and carry.

The GARCH conditional standard deviation sigma measures the uncertainty of price or interest rate changes, and a larger value indicates stronger volatility. The sigma of the stock index and the exchange rate is expressed in percentage terms and that of the two interest rates in basis points, with full-sample means of 1.674, 0.135, 8.727, and 2.876, respectively. Each market's volatility is measured in its own unit, and cross-market predictive contributions are compared in DY shares; the

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exchange rate sigma describes the volatility of the central parity rate, and the long-term sigma describes the volatility of the government bond yield.

The marginal GARCH parameters are estimated over the full sample; after extracting daily sigma, the vector autoregression (VAR) underlying the DY index is estimated over rolling windows. This procedure is used to review the volatility linkages within the sample period, and its real-time early warning performance is left for future research.

4. Model specification and diagnostics

4.1. GARCH extraction and DCC

To unify the volatility measure, all four marginal models use sGARCH(1,1) with standardized Student-t innovations [5, 6]. The conditional mean is constant for the stock index and the exchange rate, and includes an AR(1) term for the changes in the two interest rates. Let m denote the conditional mean, epsilon the residual, sigma the conditional standard deviation, and z the standardized innovation; the marginal specification is given by equations (1) and (2):

$$x_{i,t} = m_{i,t} + \varepsilon_{i,t},\ \varepsilon_{i,t} = \sigma_{i,t} z_{i,t} \tag{1}$$

$$h_{i,t} = \omega_i + \alpha_i 2_{\varepsilon}^{i,t-1} + \beta_i h_{i,t-1},\ \sigma_{i,t} = 1/2_{h}^{i,t} \tag{2}$$

The models are solved with the hybrid algorithm and scaled data, and the convergence code is zero for all four series after imposing the variance stationarity constraint. Table 2 reports the point estimates; complete standard errors and daily sigma are stored in the replication attachment. The parameter mu is recorded under the rugarch mean parametrization, and the AR1 term applies to the two interest rate series.

Table 2. Marginal GARCH parameters

Market	mu	AR1	omega	alpha	beta	nu
Stock	0.0783	—	0.0230	0.0839	0.9151	3.9732
Exchange rate	0.0051	—	0.0004	0.3004	0.6986	4.5667
Short-term rate	0.1384	0.4420	0.0586	0.3400	0.6590	2.7184
Long-term rate	−0.1093	0.1452	0.2370	0.0849	0.8933	5.4171

The sum of alpha and beta is about 0.999 for the stock index, the exchange rate, and the short-term rate, and 0.978 for the long-term rate, reflecting high volatility persistence. The lowest p-values of the 10th-order Ljung-Box test on residuals, the 10th-order test on squared residuals, and the 5th-order ARCH LM test are 0.156, 0.661, and 0.370, so no significant remaining correlation or ARCH effects are found at the lags examined. The marginal parameters satisfy the stationarity constraint, which is tested separately from the stationarity of the extracted sigma series (see Section 4.2).

The DCC part uses the same marginal fits and estimates a joint DCC(1,1) model from the standardized residuals of returns and interest rate changes [8], with a multivariate t distribution and the solnp solver. Let D denote the diagonal matrix of sigma and Q-bar the sample covariance of the standardized residuals; the specification is given by equations (3) to (5):

$$H_t = D_t R_t D_t,\ z_t = -1_{D}^{t} \varepsilon_t \tag{3}$$

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$$Q_t = (1 - a - b)\overline{Q} + az_{t-1}{}'_z{}^{t-1} + bQ_{t-1} \tag{4}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{5}$$

The estimates are a = 0.0176 (standard error 0.0104) and b = 0.8990 (0.0729), with a + b = 0.9166; the degrees of freedom of the multivariate t distribution are 4.9693 (0.3174), the convergence code is zero, and the smallest eigenvalue of the correlation matrix is 0.7318. The p-value of a is 0.090, and the constant correlation test statistic is 0.998 with p = 0.607, so constant correlation is not rejected and the evidence for time variation is weak. Accordingly, the DCC path and the window means are used only as descriptions of co-movement.

4.2. Conditional volatility DY

The input v of the DY spillover index is the level of the four conditional standard deviations sigma [12, 13]. The VAR includes a constant and no trend, and the baseline setting uses lag order p = 2, forecast horizon H = 10, and rolling window W = 200, where B denotes the coefficient matrix at lag l, with the window moving forward by one observation each day, as shown in equation (6):

$$v_t = (\sigma_{1,t}, \ldots, \sigma_{4,t})', \; v_t = c + p\sum_{\sum}^{l=1} B_l v_{t-l} + u_t \tag{6}$$

Let V denote the covariance matrix of the VAR residuals, A the moving average coefficient matrices with A0 equal to the identity matrix, and e the selection vector. Generalized forecast error variance decompositions [10, 11] are used and normalized by row, which avoids the dependence of the Cholesky decomposition on variable ordering, as shown in equations (7) and (8):

$$\theta_{ij}(H) = \frac{-1_V^{jj} H-1\sum_{\sum}^{s=0} ({}'_e{}^i A_s V e_j)^2}{H-1\sum_{\sum}^{s=0} {}'_e{}^i A_s V {}'_A{}^s e_i} \tag{7}$$

$$\tilde{\theta}_{ij} = \frac{\theta_{ij}}{4\sum_{\sum}^{j=1} \theta_{ij}} \tag{8}$$

Directional and total indicators are constructed from the normalized shares, as shown in equations (9) and (10):

$$FROM_i = 1004\sum_{\sum}^{j \neq i} \tilde{\theta}_{ij}, \; TO_i = 1004\sum_{\sum}^{j \neq i} \tilde{\theta}_{ji} \tag{9}$$

$$NET_i = TO_i - FROM_i, \; TCI = \frac{1}{4} 4\sum_{\sum}^{i=1} FROM_i \tag{10}$$

Row i represents receiving and column j represents sending, and the weight of the edge from j to i is 100 times the normalized share. TO and FROM are measured in percentage points for each node; the total connectedness index (TCI) is the average of the four FROM values, and the NET values sum to zero. The computational error of an independent replication is below 1e-12. The implementation uses rugarch 1.5.6, rmgarch 1.4.3, and ConnectednessApproach 1.0.4, and reports the standard TCI; the latter deducts p observations internally, so passing window.size = 202 under the baseline yields an actual window of 200 observations, dated at the last day of the window.

Before entering DY estimation, the stationarity of the input series and of the rolling VAR are examined separately, and Table 3 reports the diagnostics.

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Table 3. Stationarity diagnostics of conditional volatility

Market	ADF statistic	ADF lag	KPSS p-value
Stock	−1.906	1	0.022
Exchange rate	−6.522	1	≤0.010
Short-term rate	−4.512	4	≤0.010
Long-term rate	−2.965	1	0.045

Note: The ADF test includes a constant with a maximum lag of 10 selected by BIC and a 5% critical value of −2.86; the KPSS test takes level stationarity as the null hypothesis.

Table 3 shows that, for the sigma level series, the ADF test does not reject a unit root for the stock index while it rejects for the other three series, and the KPSS test rejects level stationarity for all four series, so stationarity of the inputs is not uniformly supported. It should be noted that neither the variance stationarity constraint of the marginal GARCH models nor the eigenvalue condition of the VAR can substitute for these tests. As far as the DY framework itself is concerned, the largest eigenvalue of the full-sample VAR(2) is 0.981, below one, so the baseline DY model satisfies the stationarity requirement over the full sample; AIC, HQ, and FPE select VAR(2) while BIC selects VAR(1); the p-values of the 16th- and 20th-order Portmanteau tests are 0.613 and 0.238, and that of the 5th-order Breusch-Godfrey test is 0.386.

In rolling estimation there are 533 windows of 200 days, of which 13 have a largest eigenvalue greater than or equal to one (10 and 13 July during the crisis) and are excluded; the main text summarizes 520 stable windows, of which 53 fall in the crisis period, while all windows are retained for comparison. The 16th- and 20th-order tests still reject no autocorrelation in 175 and 270 windows, respectively. This filter addresses eigenvalue instability only, and input stationarity and residual diagnostics remain specification limitations, so the results below are positioned as in-sample exploratory descriptions.

5. Empirical results and economic interpretation

5.1. Conditional volatility and correlations

Figure 1 shows the time paths of the GARCH conditional volatilities of the four markets. The volatility peaks of the four markets are not synchronized, indicating that the time distribution of uncertainty differs across markets. DCC describes how returns and interest rate changes move together, whereas the DY index of conditional volatility describes the predictive contribution of one market's volatility to the future volatility of another market.

Taking 15 June as the onset of the crash and excluding that day, the window means of DCC are compared over the five or ten common trading days before and after; Table 4 reports this descriptive comparison.

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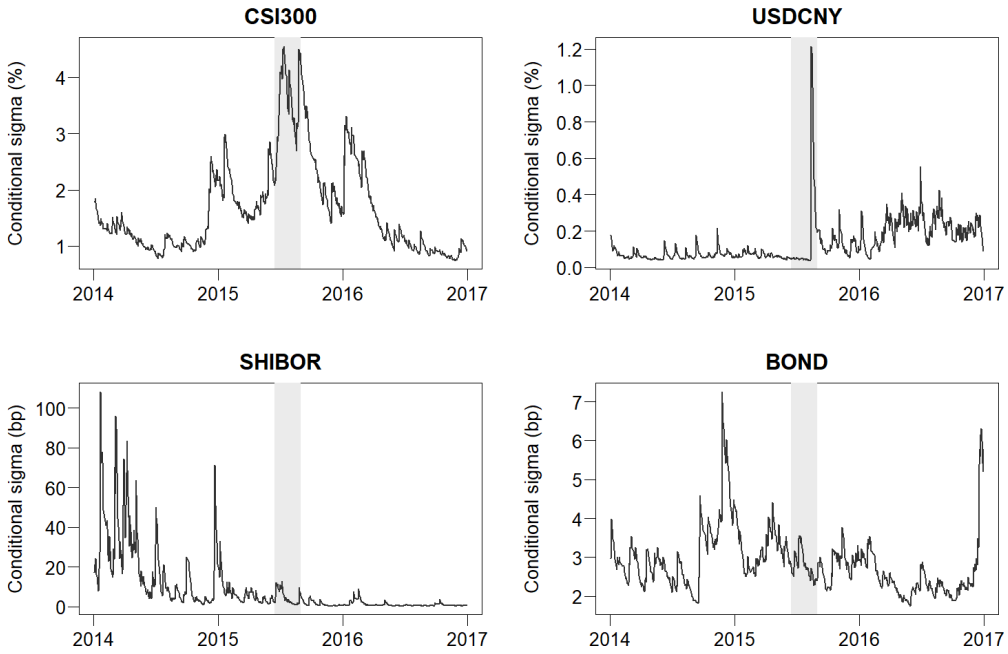


Figure 1. GARCH conditional volatilities of the four markets

Note: Shaded areas cover 15 June to 31 August 2015; each panel uses the volatility unit and vertical axis scale of the corresponding market.

Table 4. DCC correlations before and after the onset of the crash

Variable pair	10 days before	10 days after	10-day difference	5-day difference
Stock and exchange rate	0.001	0.022	0.021	0.012
Stock and short-term rate	−0.015	−0.077	−0.062	−0.039
Stock and long-term rate	−0.038	−0.001	0.036	0.019

Over the ten days before and after, the average DCC between the stock index and the short-term rate falls from −0.015 to −0.077, that between the stock index and the exchange rate rises from 0.001 to 0.022, and that between the stock index and the long-term rate rises from −0.038 to −0.001. Within the windows, a deepening negative correlation, a weak positive correlation, and a convergence of a negative correlation toward zero are observed, respectively, and the directions of the mean changes are consistent in the five-day window. These mean differences describe changes in co-movement only and have not been tested for significance.

5.2. Total spillovers and the directional network

Figure 2 summarizes the time paths of DCC correlations and of the DY total volatility spillover. The TCI of the full-sample VAR is 2.392%, and the average over all stable rolling windows is 6.826%; the average is 7.420% from 1 January to 12 June 2015 and 4.260% from 15 June to 31 August, with a local peak of 20.323% on 13 August. Under the 200-day window the average contribution share during the crisis is lower, while local high values are present; the crisis mean over all windows is 4.268%, close to that over stable windows.

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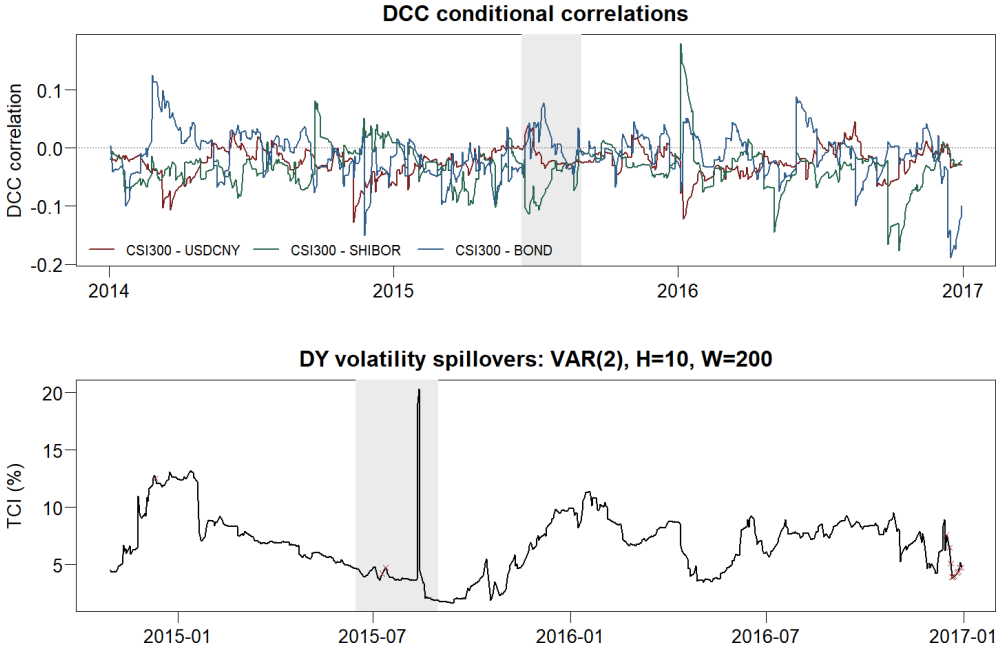


Figure 2. DCC correlations and the DY total volatility spillover

Note: The lower panel retains all windows for diagnostics; red crosses denote unstable windows, which are excluded from the statistics reported in the main text.

The TCI is the average share of external forecast error contributions received by each market when H = 10, measured in percentage points; sigma describes the scale of volatility and the TCI describes the proportion of external sources. Each rolling point uses the preceding 200 observations, and the peak date is the last day of that estimation window. Table 5 reports the average directional spillovers within crisis-stable windows.

Table 5. Average directional volatility spillovers in crisis-stable windows

Market	TO	FROM	NET
Stock	3.238	9.908	−6.670
Exchange rate	7.171	2.482	4.689
Short-term rate	2.395	2.784	−0.389
Long-term rate	4.237	1.867	2.370

In crisis-stable windows the average net sending of the exchange rate and the long-term interest rate is 4.689 and 2.370 percentage points, respectively, while the average net receiving of the stock market and the short-term interest rate is 6.670 and 0.389 percentage points. Net sending means that the contribution to others exceeds the contribution received. The exchange rate and the long-term rate are net senders in 79.2% and 96.2% of the windows, respectively, and the stock market is on average a net receiver; the net value of the short-term rate is close to zero and is positive in 56.6% of the windows, so its role changes across phases.

Figure 3 presents the average predictive contributions in crisis-stable windows as a network. The two largest external contributions in the network are from the exchange rate to the stock market at

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5.948 percentage points and from the long-term interest rate to the stock market at 2.795 percentage points, accounting for about 5.95% and 2.79% of the stock volatility forecast error, respectively. This indicates that in the model the external contributions to stock market volatility come mainly from the exchange rate and the long-term interest rate; the results suggest that the volatility of the central parity rate and of the long-term interest rate may be monitored when tracking stock market volatility, while the economic mechanism requires further testing with capital flow and other data.

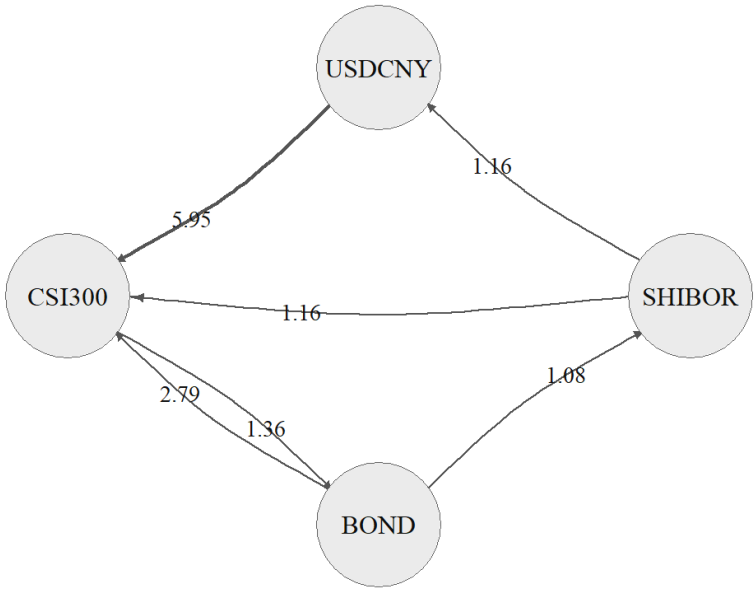


Figure 3. Predictive contribution network of conditional volatility during the crisis

Note: Edge weights are in percentage points and the plotting threshold is 1; statistical indicators use the complete matrix and nodes are of equal size.

6. Robustness and descriptive event-window comparisons

This section examines the sensitivity of the baseline results to alternative specifications and provides descriptive comparisons for key event windows. Table 6 summarizes the conditional volatility DY results under alternative lag orders, forecast horizons, window lengths, and marginal model choices.

Table 6. Alternative specifications of the conditional volatility DY

Specification	Pre-crisis mean	Crisis mean	Crisis peak
P2 H10 W200	7.420	4.260	20.323
P1 H10 W200	6.273	3.553	21.013
P4 H10 W200	8.105	5.947	23.367
P2 H5 W200	4.225	2.439	14.903
P2 H20 W200	12.794	8.515	24.515
P2 H10 W150	7.408	10.227	40.670
P2 H10 W100	11.427	19.625	22.609

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Table 6. (continued)

BIC marginal alternative W200	6.995	4.120	22.534

Note: All rows use stable windows and the same pre-crisis interval. The crisis mean under the W100 specification uses 40 windows, while the other specifications use 51 or 53 windows.

When the VAR order is changed to one or four, the crisis mean under the 200-day window remains lower than the pre-crisis mean, and the contribution share rises as the forecast horizon H increases from 5 to 20. When the window length W is 150 or 100, the crisis mean is higher than the pre-crisis mean, showing that the phase comparison is sensitive to the window setting. Under the W100 specification the peak across all windows is 72.062% and comes from an unstable window, whereas the stable-window peak is 22.609%, which Table 6 uses.

Among 36 candidate fits combining sGARCH, GJR-GARCH, and EGARCH with t, GED, and normal innovations, convergence, persistence below one, and p-values above 0.05 for three residual tests are required first, after which the BIC of each series is used for selection. The stock index switches to sGARCH-GED and the short-term rate to GJR-GARCH-GED, while the other two series remain sGARCH-t; the crisis mean under the alternative specification is 4.120% and the peak is 22.534%, and the average directions of net receiving for the stock market and net sending for the exchange rate and the long-term rate are unchanged.

Policy and market events are further used as anchors to compare mean changes in DCC and in the TCI within short windows before and after each event, and Table 7 reports the results.

Table 7. Descriptive comparison of event-window mean differences

Event anchor	Stock-short DCC 5 days	Stock-short DCC 10 days	TCI 5 days	TCI 10 days
Joint window 29 June	0.014	−0.024	0.454	−0.102
Joint window 6 July	−0.006	0.013	−0.850	−0.361
Exchange rate reform 11 August	0.006	−0.005	6.473	2.378
Alternative anchor 30 June	0.001	−0.020	0.290	−0.073

Note: Differences are the after mean minus the before mean, and TCI is in percentage points; the TCI five days after 6 July uses only 3 stable windows and the ten days after 29 June, 6 July, and 30 June use only 8 windows, while the remaining cells are complete. All DCC cells use complete windows.

For the onset of the crash, the mean difference of the TCI, after minus before, is −0.443 and −0.727 percentage points over the five- and ten-day windows, while after the exchange rate reform it is +6.473 and +2.378 percentage points, so an increase in the within-window mean of the TCI is observed for both reform windows. For the TCI and the stock-short-term DCC at the 29 June anchor and for the stock-short-term DCC at the 6 July anchor, the sign of the difference changes with the window length. These mean differences have not been tested for significance and only describe changes around the events.

Event dates are recorded according to announcements, effective dates, and trading days. The central bank announced interest rate and targeted reserve requirement ratio cuts on 27 June, effective on 28 June, and the anchor is taken as 29 June; the measures for the administration of investment of basic old-age insurance funds were released for public consultation on 29 June. In the evening of 4

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July, 28 IPO candidates announced the suspension of issuance, and on 5 July the CSRC issued an announcement of liquidity support to China Securities Finance Corporation, the two pieces of information being combined into the 6 July window.

The measures for the administration of investment of basic old-age insurance funds were drafted on 17 August and publicly released on 23 August, and the RMB central parity reform on 11 August is treated as a separate window. The verification of the exact consultation time is limited, and 30 June is therefore used as an alternative anchor. The events overlap, so this paper reports the joint changes in the corresponding windows; these descriptive comparisons do not control for other contemporaneous information, and the effect of individual policies is left to mechanism testing.

7. Conclusion

Under the sample and model settings of this paper, the average predictive contributions in crisis-stable windows differ in direction: the volatility of the exchange rate and the long-term interest rate is a net sender, while stock market volatility is a net receiver. The average contribution of the exchange rate to the stock volatility forecast error is 5.948 percentage points and that of the long-term interest rate is 2.795 percentage points, making them the two main external predictive sources. The results suggest that the volatility of the central parity rate and of the long-term interest rate may be monitored when tracking stock market volatility.

Under the 200-day window the crisis average TCI is 4.260%, below the pre-crisis 7.420%, with a local peak of 20.323% on 13 August; under the 150-day and 100-day windows the crisis mean is higher than the pre-crisis mean, showing that the phase comparison depends on the time scale. The average TCI over both the five- and ten-day windows rises after the exchange rate reform, which is a descriptive observation. This paper provides evidence on the direction and time distribution of predictive contributions to volatility; the limitations regarding input stationarity, rolling residuals, and evidence on DCC time variation are reported in the diagnostics, and further verification requires structural change and capital flow data.

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