Asymmetry and non-normality in the dynamics of Chinese renminbi markets

Jie Li\textsuperscript{a} and Aaron D. Smallwood\textsuperscript{b}

Abstract:

In studying the evolving relationship between onshore and offshore RMB exchange rate returns, we implement a novel approach that allows for asymmetry in volatilities and idiosyncratic deviations from normality. Specifically, for a complete set of rolling subsamples, we use the multivariate skew student density function coupled with the asymmetric BEKK model to simultaneously estimate mean and variance equation spillover effects. The results show consequential differences in distributional parameters, where leptokurtosis is a more dominant feature in offshore returns for the most recent samples. Further, while price discovery now appears to largely run from offshore to onshore markets, bidirectional volatility spillovers exist, where asymmetry is shown to have vital implications. Particularly after the August 11, 2015 reform, estimation of the systems and the use of volatility impulse response analysis reveal that the onshore market are especially susceptible to offshore shocks under an RMB depreciation.

Keywords: Onshore and offshore RMB spillovers, asymmetric BEKK, multivariate skew student density function

JEL Codes: F31, F33, C32

\textsuperscript{a}. College of Economics and Management, Nanjing University of Aeronautics and Astronautics, 29 Jiangjun Avenue, Jiangning District, Nanjing 211106, Peoples Republic of China. Email: jieli@nuaa.edu.cn

\textsuperscript{b}. Department of Economics, University of Texas-Arlington, 701 South West Street, Campus Box 19479, Arlington, TX, 76019, United States. Phone (817) 272-3061. Email: smallwood@uta.edu. (Corresponding author)

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I. Introduction

Since 2010, the renminbi (RMB) has emerged as one of the world’s most important and dynamic currencies. Internationalization of the RMB has accelerated causing China’s currency to move from being virtually untraded outside of national borders at the start of the century to being the eighth most actively traded in the world according to the 2019 Bank for International Settlements Triennial Survey (see, https://www.bis.org/statistics/rpfx19.htm). The ascendancy of the RMB has coincided with the emergence of offshore trading, which started in August 2010. Given existing capital controls and a desire for stability on the mainland, coupled with a largely unregulated offshore market, potentially fragmented markets have developed for onshore (CNY) and offshore (CNH) renminbi.

The existence of two markets for the yuan has implications for policy makers and researchers. For one, segmented markets could support a gradual move toward financial liberalization in China. It has been surmised that CNH markets could serve as a vehicle for expanding global use of the RMB, while potentially providing market-oriented information that contributes to price discovery in onshore markets (see, Maziad and King, 2012, and Cheung and Yiu, 2017). At the same time, integration between the CNH and CNY exchange rates potentially allows for the transmission of shocks between these markets that can result in increased volatility when spillovers exist (Funke et al, 2015). A rise in volatility in one market could have consequences for the other, with obvious implications for currency traders and policy makers. Anecdotally, unexpected RMB weakness emanating from offshore markets could have a relatively large impact. In one high-profile episode in January 2016, speculators initiated heavy trading in offshore RMB resulting in capital outflow and a spike in volatility in the onshore
market. Ultimately, traders suffered massive losses following a rumored intervention by the PBoC.¹

In isolating relationships between CNH and CNY returns themselves, conventional VAR and Granger casualty analysis has generally yielded only modest evidence of a relationship (see, Wu and Pei, 2012, Maziad and Kang, 2012, Cheung and Rime, 2014, Ding et al., 2014, and Zhao et al., 2021).² Research has also addressed the extent to which changes in policy and economic shocks impact exchange rate differentials and their volatilities. Of note, Funke et al. (2015) show that to a large extent offshore liquidity drives differentials, particularly during times of global instability. At the same time, increased RMB liberalization is shown to reduce volatility. Liang et al. (2019) further contribute to this line of research, considering several important policy changes including the exchange rate reform introduced by the PBoC on August 11, 2015 (hereafter “811-reform”).³ The authors consider several GARCH methods, including the threshold model of Glosten, Jaganathan, and Runkle (1993), and show that reforms may both lower the pricing differential and increase its associated volatility. Sun et al. (2020) present somewhat contrasting evidence using interval time series models, where the impact of fundamentals on RMB dynamics changes after the 811-reform, although the underlying price dynamics are largely unaffected.

Several studies have specifically analyzed the relationship between CNH and CNY volatilities using multivariate GARCH methods, including Maziad and Kang (2012), Liang et al. (2019), and Funke et al. (2020). Maziad and Kang use the BEKK model of Engle and Kroner

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² Xu et al. (2017) use a thermal optimal path method and argue that CNY and CNH exchange rates show a weak alternate lead-lag structure in most time periods. Several additional studies also consider the relationship between onshore and offshore spot and forward rates. See, for example, Leung and Fu (2014) and Ho, Shi, and Zhang (2018).
³ In another important strand of the literature, Marconi, (2017), Keddad (2019), and McCauley and Shu (2019) study the movement between the RMB and other currencies, including those from emerging markets (EM). McCauley and Shu (2019) consider both the CNY and CNH exchange rates, showing that higher correlation results between RMB and EM returns when CNY exchange rates replace CNH counterparts.
(1995) and document a stronger cross-equation impact of CNH volatilities for their second subsample starting in 2011. Liang et al. (2019) also find evidence of a time-varying relationship in the conditional correlation of returns using the DCC model introduced by Engle (2002). Funke et al. (2020) propose a novel Bayesian estimation method applied to the BEKK model that can be used to construct confidence bands about volatility impulse response functions. The authors document stronger spillover from the CNY volatilities to CNH counterparts for the full sample, while also providing evidence related to historical shocks. Most notably, the 811-reform generates a shock that has a considerably large impact on the CNH-based volatility.

Many of the referenced studies above highlight challenges in studying the dynamics of the RMB. Most notably, asymmetry is likely to be an important feature of RMB volatilities, as market participants and policy makers may respond differentially to unexpected yuan strength relative to weakness (see, for example, Liang et al. 2019). Additionally, the assumption of normality is nearly certain to be violated when applying various econometric methods to exchange rates and specifically RMB-based returns (see Susmel and Engle, 1994 and Funke, et al. 2020). For example, there is strong reason to suspect deviations from normality are idiosyncratic for CNY and CNH returns given that PBoC influence could be expected to mitigate extreme changes in the CNY series typically associated with leptokurtosis. Although QMLE-based estimation could be consistent, inefficient parameter estimation almost certainly results when a Gaussian assumption is imposed. Finally, a myriad of important policy changes and the continued growth of offshore yuan markets necessitates methods that can accommodate the constant evolution of the relationship between onshore and offshore markets. The links between markets may be expected to be time varying, depending on the underlying policy stance at the time. In terms of the exchange rates themselves, Cheung and Rime (2014) found strong evidence
of cointegration, where in early samples CNY returns were found to be weakly exogenous. These authors also provided evidence of a time-varying short-run relationship, where strong evidence of spillovers from CNY to CNH returns was reversed in the last subsample considered.

In this paper, we simultaneously overcome all concerns raised above through the application of a full-VECM system for CNH and CNY returns applied to rolling subsamples covering all observations in our data set running from August 2010 through July 2020. In all cases, multivariate GARCH effects are modelled in disturbances using the asymmetric extension of the BEKK method first analyzed by Grier at al. (2004). Further, joint estimation of all model parameters occurs using maximum likelihood estimation based on the multivariate skew student density function initially proposed by Bauwens and Laurent (2005). The distributional assumption allows for idiosyncratic skew and kurtosis in the underlying returns and was shown to yield improved Value-at-Risk forecasts for exchange rates by Bauwens and Laurent. The employed distribution is not only implemented to provide more realistic distributional assumptions and efficient parameter estimates. Independently, the algorithms yield estimates connected to higher order central moments that can be used to understand differences more fully between onshore and offshore markets. Finally, in addition to reporting coefficient test results related to spillover effects, we use computational methods to calculate generalized and volatility impulse response functions for a variety of shocks. We believe our approach in this context is quite novel. We are unaware of any study of the relationship between RMB onshore and offshore markets that implements a rolling sample approach to account for parameter instability in a model that combines a VECM system with a multivariate GARCH model. Additionally, our paper is the first to analyze full multivariate asymmetric impacts for the conditional variance matrix, while also employing extremely general distributional assumptions.
Our primary findings can be summarized as follows. Whereas evidence from earlier subsamples suggests that CNY returns are weakly exogenous, findings for the more recent periods show a higher propensity for both series to respond to disequilibria. There is also strong evidence that when short-run mean equation spillovers exist, price discovery is now substantially more likely to occur in onshore markets relative to offshore counterparts. Spillover impacts, both for the mean and variance equations, are strengthened in the immediate aftermath of the 811-reform. We also show that distributional parameters converged during this time-period, although both the skewness and degree of freedom parameters diverge considerably for other samples. Most notably, the implied kurtosis for CNY returns is much lower than offshore counterparts during the recent subsample, possibly suggesting that monetary authorities use price discovery in a way that minimizes extreme fluctuations in the domestic exchange rate. Even still, in the most recent sample, we provide evidence to show strong CNH-based volatility and shock spillovers to the onshore market. Perhaps more importantly, the results clearly show that asymmetry is an increasingly important feature of volatility dynamics for the RMB, with vital implications for the currency. Most notably, the use of our VIRFs reveals that CNH spillovers tend to dominate under negative shocks, with CNY returns driving impacts under positive shocks.

The rest of the paper is organized as follows. In Section 2, we provide an overview of the changing political and economic landscape associated with the RMB. Section 3 provides a discussion of our data and provides preliminary data analysis. This section also discusses our methodology. Section 4 includes our estimation and parameter testing results, and section 5 details our GIRF and VIRF analysis. A final section concludes.

2. Background

To a large extent, RMB internationalization was formalized as a concept following the 2007-08
global financial crisis, whereupon it seemed natural to envision a financial system less reliant on the US dollar. Given the ambition of policy makers within the PBoC and the sheer size of the Chinese economy, many envisioned a tripolar monetary system where the RMB could eventually dominate within Asia (see Fratzscher and Mehl, 2014 and Ito, 2017). Numerous financial shocks and policy changes have transpired since 2009, altering the extent to which internationalization has been realized and laying the foundation for the current bifurcated status of the RMB. Cross border settlement in RMB began with a small number of currencies in 2009, but quickly expanded such that full current account convertibility has largely been achieved. Capital account liberalization needed for full functioning of a thriving offshore market has been slower to materialize. In a major step, in December 2011, China added the RMB qualified foreign institutional investor (RQFII) program to allow foreigners using offshore RMB accounts to invest in onshore RMB bond and equity markets that were initially subject to strict quotas. In September 2013, the Shanghai Free-Trade Zone was established, while stock connect programs between Hong Kong and both Shanghai and Shenzhen were established in November 2014 and December 2016, respectively. These programs allow investors in each market to trade on the other stock market. To open up domestic investment, the RMB qualified domestic institutional investor (RQDII) program was launched in November 2014, although concerns regarding capital flight after the 811-reform led to a suspension of granted quotas. The program was reinitiated in May 2018, with specific rules limiting the ability to trade RMB for foreign currencies.\footnote{The program complemented the existing QFII scheme formed in 2002. Over time, rules have been relaxed, and in May 2020, quotas were lifted altogether. Further, in November 2020, the RQFII and QFII programs merged. Specific details can be found through the State Administration of Foreign Exchange (SAFE: https://www.safe.gov.cn/en/2020/0507/1677.html) and the China Securities Regulatory Commission (CSRC: http://www.csrc.gov.cn/pub/cscc_en/newsfacts/release/202009/t20200925_383652.html).}

\footnotetext[5]{See https://www.globaltimes.cn/content/1100615.shtml. Programs favoring outbound direct investment under QDII and QDII2 were also initiated in January 2011 and June 2015. See Liang et al. (2019) for more detail on these and other policy changes related to capital flows.}
Rules governing interbank RMB trading in the onshore market have evolved concurrently with the changes to the environment governing capital flows in and out of China. Notably, after a brief period of pegging during the global financial crisis, the onshore rate has gradually become more market oriented. For example, trading bands relative to the central parity rate against the US dollar were widened from 0.50% to 1% on April 16, 2012, before reaching 2% on March 17, 2014. In the aftermath, market forces frequently moved onshore rates close to trading limits before rates were subsequently reset the following day. To align the central parity rate more closely with market conditions, a first major change to policy occurred on August 11, 2015. The PBoC announced that the closing price from the most recent trading day would serve as an important reference in setting the parity rate, with additional weight placed on exchange rate movements in the currencies of trading partners. The announcement may not have had the intended effect as the RMB sharply lost value in what ultimately was seen by policy makers as a self-reinforcing mechanism (see, McCauley and Shu, 2019). Subsequently, new capital controls stemmed capital outflow, while the PBoC moved to provide more guidance.6

The second major policy change occurred when a countercyclical factor was added to the mechanism establishing the daily parity rate on May 25, 2017. The countercyclical variable was included to offset perceived herding behavior and overshooting that may have been present when daily parity rates heavily weighted the previous trading days’ closing price.7 Although some market participants may have felt that these changes did not result in a more market-oriented

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6 Additional changes have been implemented by the China Foreign Exchange Trade System (CFETS). In early 2017, the reference basket used by the PBoC expanded from 13 currencies to 24. Additionally, the window for reference to the currencies of trading partners was reduced from 24 to 15 hours in February 2017.

7 Under modified rules, the PBoC can activate or suspend the countercyclical factor under different market situations. For example, the mechanism was suspended on January 8, 2018, and then reinstated on August 24, 2018. Subsequently on October 27, 2020, the CFETS announced that the countercyclical factor would be implemented less (see, https://www.reuters.com/article/china-markets-pboc/exclusive-china-asks-banks-to-suspend-counter-cyclical-factor-in-yuan-fixing-sources-idUKL1N2HI0PX).
central parity rate, policy makers believed the mechanism could be implemented to smooth exchange rate movements when changes did not otherwise reflect economic fundamentals.

Clearly, the degree of integration and underlying factors impacting the relationship between the CNH and CNY exchange rates have constantly evolved since 2010. Among these changes, two major Chinese policy events stand out, including the 811-reform and the implementation of the new countercyclical factor in central parity pricing. Our analysis below accommodates constant change in the underlying relationship using rolling subsamples, where we group all findings according to their temporal relationship with these monumental policy shocks. More specifically, estimation results for any subsample ending prior to the 811-reform are labelled “pre-811,” where corresponding findings after May 25, 2017 are denoted “CCF-period.” Finally, the sample between these two events is labelled “transition-period.” We now turn to a full discussion of our data and associated methodology.

3. Data and Methodology

3.1. Data

We use the daily closing spot USD prices of the RMB for both onshore and offshore markets. Coinciding with the formal launch of the CNH market, our data begins on August 23, 2010, ending on July 17, 2020. After taking log differences of the exchange rates and eliminating data due to holidays and weekends, we have a total of 2421 observations. Here, the log exchange rates of onshore and offshore markets are denoted by $s_t^{CNY}$ and $s_t^{CNH}$, respectively, where $r_t^{CNY}$ and $r_t^{CNH}$ yield corresponding returns, with $r_t^i = 100(s_t^i - s_{t-1}^i), i=CNY,CNH$. The original data is provided by Bloomberg.

In Table 1, we provide some relevant summary statistics for our data, both for the full sample period and the relevant subsamples as discussed above. The preliminary analysis demonstrates that unconditional moments are potentially time varying. Whereas the earliest
subsamples were characterized by a relatively low unconditional standard deviation in both return series, later samples appear to be more volatile. Additionally, even for the original unfiltered returns series, there is evidence of both evolving skewness and kurtosis and differences in these higher order central moments across CNY and CNH returns. For example, a much larger sample kurtosis is observed for CNH returns in the earliest subsample.

Given the constant evolution of exchange rate policy and the preliminary results from above, we consider rolling subsamples and employ very flexible distributional assumptions as more formally defined below. In terms of the rolling subsamples, we consider a sequence of 2182 samples, initially using 240 observations, corresponding to roughly one year of trading data. To be specific for the first subsample, we jointly estimate model parameters using data from August 24, 2010 through August 1, 2011. The subsequent subsample uses 240 observations from August 25, 2010 through August 2, 2011 and the procedure continues until the end of the sample is reached. To demonstrate, Figure 1 shows our full sample of returns, emphasizing three subsamples in boxes.

Several pretests are needed before turning our attention to the complete methodology. We first begin with a discussion of the problematic assumption of normality for raw returns for each of our subsamples. In Figure 2, we depict the sample kurtosis and sample skewness with dates corresponding to the last observation for each of our 2182 periods. The more granular evidence here matches the discussion above, where the findings show both evolving central moments and sometimes stark differences between the sample kurtosis and skewness of CNY returns versus those of CNH returns. More formal Jarque-Bera test statistics, which are available on request, provide resounding evidence against the Gaussian assumption for each series. More specifically,

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8 The use of rolling subsamples for financial data with an unknown number of breaks is very common within the literature. See, for example, Yu, Fang, and Tam (2010).
based on a 5% test-size, there are only 43 cases where we fail to reject the joint hypothesis of zero skew and a kurtosis of 3 for CNY returns, with only 13 such instances for the corresponding CNH series. In summary, the preliminary evidence shows very strong evidence against normality for returns with time-varying leptokurtosis and negative skew. Finally, we see from Figure 2 that for most subsamples, an assumption of constant kurtosis and skewness across both series seems questionable at best.

Below, we estimate a system based on a reduced-form vector autoregression. In results that are available on request, necessary pre-tests using standard unit root method reveal that we generally fail to reject the unit root null for the log of the original exchange rates. Further, application of the Johansen (1991) algorithm yields overwhelming evidence favoring cointegration with a single cointegrating vector that is typically statistically indistinguishable from [1 -1]'. In what follows, we assume the log exchange rates are I(1), cointegrated series, with returns that are non-Gaussian with potentially time varying and idiosyncratic kurtosis and skew.

3.2. Methodology

Here, we describe the methodology for estimation of the model parameters used to measure mean and volatility spillovers between CNY and CNH returns. Let \( Y_t = [s_t^{CNY}, s_t^{CNH}]' \) and let \( \epsilon_t \) denote a 2x1 disturbance vector, with \( E(\epsilon_t'\epsilon_t' | \Omega_{t-1}) = H_t \), where \( \Omega_{t-1} \) is the available information set at time \( t-1 \). \( H_t \) is the conditional variance matrix. Based on the cointegration findings as discussed above, the mean equation model is given as,

\[
\Delta Y_t = c + \sum_{j=1}^{P} \Phi_j \Delta Y_{t-j} + A(s_{t-1}^{CNY} - s_{t-1}^{CNH}) + \epsilon_t, \tag{1}
\]
where $c$ is a vector of constants and $\Lambda$ is a 2x1 vector of speed of adjustment parameters. The appropriate lag-order $P$ is obtained via minimization of the Schwarz Bayesian Information Criterion, which supports $P=1$ in a plurality of samples.\(^9\)

To parameterize $H_t$, we employ the asymmetric extension of the BEKK model of Engle and Kroner (1995). The use of multivariate GARCH methods, and specifically the BEKK model, has a rich tradition in studying the interconnectivity between markets (see, for example, Baele (2005), Efimova and Serletis (2014), and Kocaasrslan et al. (2017), amongst others). For financial assets, asymmetry in the elements of $H_t$ appears to be an especially relevant feature (Susmel & Engle, 1994). Specifically, for RMB-based exchange rates, an asymmetric response to unexpected depreciations associated with negative shocks is potentially relevant, particularly for recent subsamples. More specifically, we posit asymmetry is likely to be especially important for onshore markets for later subsamples. For the earliest part of our full sample, Chinese policy makers generally pursued an unabated, and arguably predictable, gradual appreciation of the RMB. More recently, internalization of the RMB and a more market-oriented exchange rate are likely to contribute to an environment where unexpected depreciations trigger a differential volatility response. The asymmetric BEKK model can be written as,

$$H_t = CC' + A\varepsilon_{t-1} \varepsilon'_{t-1} A' + BH_{t-1} B' + D Z_{t-1} Z'_{t-1} D'.$$

Here $C$ is a lower triangular 2x2 matrix of constants and $Z_t = I(\varepsilon_{t<0}) \circ \varepsilon_t$, with $I$ denoting the indicator function and where “$\circ$” yields the Hadamard product. $A$, $B$, and $D$ are 2x2 coefficient matrices, whose off-diagonal elements can be used to measure spillover impacts. For example,

\(^9\) Specifically, a value of 1 was selected for 1107 subsamples, with the BIC favoring $P=2$ for another 594 periods. For consistency, we set $P=1$, throughout, although similar conclusions were reached when setting $P=2$. 
the row-1, column-2 element of each matrix can be used to test the hypothesis of no CNH-based spillover to the CNY-based conditional variance.

In terms of the distribution of $\epsilon_t$, most studies employ a Gaussian assumption, employing quasi maximum likelihood estimation (QMLE) and the use of robust standard errors based on Bollerslev and Wooldridge (1992). Although QMLE may be expected to be consistent under a symmetric distribution, deviations from normality can yield inefficient parameter estimates. In a univariate context, Engle and Gonzalez-Rivera (1991) demonstrated that the problem was especially severe when departures from normality were substantial, as seems to be relevant for many analyzed subsamples here. Additionally, there is likely to be independent interest in the time-varying idiosyncratic evolution of the kurtosis and skewness of CNY and CNH returns. Finally, we are interested in modelling extreme events in the context of our impulse response analysis, drawing from the empirical distributions of residuals that clearly appear to be non-Gaussian. In view of these considerations, it seems clear that a more flexible distributional approach is merited, and we therefore employ the flexible multivariate skew-Student density of Bauwens and Laurent (2005).

Here, define the 2x1 vector, $z_t$, as $z_t = H_t^{-0.50} \epsilon_t$. Given two elements, the probability density function for the multivariate skew distribution is defined as follows,

$$f(z_t) = \frac{4}{\pi} \left[ \prod_{i=1}^{2} \frac{\xi_i s_i}{1 + \xi_i^2} \Gamma\left(\frac{v_i}{2}\right) \Gamma\left(\frac{v_i + 1}{2}\right) \left(1 + \frac{\kappa_{i,t}^2}{v_i - 2}\right)^{-\frac{1 + v_i}{2}} \right],$$

where,

$$\kappa_{i,t} = \left(s_i z_{i,t} + m_i\right) \xi_i^{-i,t}.$$
\[
I_{t,t} = \begin{cases} 
1 & \text{if } z_{i,t} \geq -\frac{m_i}{s_i}, \\
-1 & \text{if } z_{i,t} \leq -\frac{m_i}{s_i}.
\end{cases}
\]

Finally, the constants \(s_i\) and \(m_i\), which represent the standard deviation and mean of the non-standardized skew-student-t density (see, Fernandez and Steel, 1998), are given by,

\[
m_i(\xi_i, v_i) = \frac{\Gamma \left( \frac{v_i - 1}{2} \right) \sqrt{v_i - 2}}{\sqrt{\pi} \Gamma \left( \frac{v_i}{2} \right)} \left( \xi_i - \frac{1}{\xi_i} \right)
\]

\[
s_i^2(\xi_i, v_i) = \left( \xi_i^2 + \frac{1}{\xi_i^2} - 1 \right) - m_i^2.
\]

The idiosyncratic degree of freedom parameters \(\nu = (\nu_1, \nu_2)\) are inversely related to the kurtosis, where a value equal to 4 implies an infinitely large kurtosis. Further, \(\xi_i^2\) can be interpreted as a measure of skewness, where values less than 1 imply negative skew, with the opposite being true for values exceeding 1.

Although multi-step procedures may be expected to yield reliable parameter estimates under a Gaussian assumption, Carnero and Eratalay (2014) demonstrate that joint estimation of mean and variance equation parameters is clearly preferred for certain multivariate GARCH structures under non-Gaussian innovations. We therefore simultaneously estimate coefficients in our VECM-MGARCH-BEKK system.\(^{10}\)

Given the definition of \(z_t\) from above, and with \(\theta\) denoting the full set of model parameters including the degree of freedom and skewness values, the log-likelihood function is given by,

\[
\log L(\theta) = \sum_{t=2}^{T} \{ \log f(z_t) - 0.50|H_t| \}.
\]

\(^{10}\) An iterative method based on a homoskedastic VAR and individual GARCH(1,1) equations is used to obtain starting values, prior to joint estimation of all model parameters using the fmincon solver within MATLAB. Relative to the default values, convergence parameters are tightened to minimize local minima and other algorithmic problems. The code, which is written by the authors, is available on request.
4. Test Results

Here, we present test results for various hypotheses related to impacts on CNY and CNH returns and their conditional variances based on equations (1) and (2) from above. Emphasis is placed on off-diagonal coefficients in relevant parameter matrices, which can be used to measure spillovers from one market to another. In all cases, the information matrix using the outer product of the score obtained in the numerical optimization above is used to construct t-statistics and Wald test statistics based on a 5% test-size.

We turn first to the results based on individual parameter estimation, concentrating on the three periods that isolate specific changes in PBoC policy related to the RMB as discussed above. Table 2 provides the proportion of test-statistics that are individually statistically significant based, whereas Table 3 provides the corresponding median parameter estimates. Although we primarily interested in potentially asymmetric impacts in the conditional variance matrix, we first turn to results for individual mean equation parameters, where several findings emerge. First, we see that in earlier samples, there is little evidence that CNY returns respond in the long run to disequilibria, yielding an initial finding of weak exogeneity in the onshore series. Of the subsamples ending prior to August 11, 2015, $\hat{\lambda}_1$ is statistically significant 11.73% of the time. The burden of adjustment clearly falls on CNH returns, where $\hat{\lambda}_2$ is statistically significant at the 5% level with near unanimity. After August 11, 2015, and especially for the most recent periods, it seems clear that the pattern has started to reverse itself, with a much higher preponderance of significant values of $\hat{\lambda}_1$, with the opposite being true for $\hat{\lambda}_2$. This finding can be more clearly seen in Figure 2, which provides estimates of the speed of adjustment parameters for every period. The figure shows values of $\hat{\lambda}_1$ that hovered near zero for most of the first subsample, yielding a somewhat counterintuitive, albeit very small, positive median estimate
equal to 0.0049. By the end of our full sample, these estimates have turned sharply negative. We further see that the influence of CNY returns on CNH markets has generally been declining, as evidenced by the parameter estimates in $\Phi_1$. In fact, for samples ending after May 25, 2017, we do not record a signal instance where lagged CNY returns significantly impact corresponding CNH values.

Turning to the distributional parameters, Figures 4a and 4b provides plots of $1/\nu_i$ and $\xi_i$, again highlighting seemingly obvious departures from normality. It is important to note that these parameter values are explicitly connected to the multivariate skewed student distribution for orthogonalized shocks estimated after accounting for mean equation and conditional variance dynamics. In short, these statistics, while obviously connected, are not expected to necessarily mirror associated kurtosis and skewness parameters for the raw returns series analyzed in the previous section.

In Figure 4a, statistics exceeding 0.25 represent a degree of freedom parameter less than 4, while values of $\xi_i$ in Figure 4b less than (greater than) 1 imply negative (positive) skew. Viewing both figures together, there are three findings that shed considerable light on the evolution of CNH and CNY returns and their relationship with each other. First, in the immediate aftermath of the 811-reform, there appears to be substantial convergence in higher order moments for CNH and CNY returns. This is especially evident from the skewness parameters in Figure 4b, where there is little discernible difference between $\hat{\xi}_1$ and $\hat{\xi}_2$. Additionally, both sets of residuals tend to have markedly similar implied kurtoses that are quite large, and potentially infinite, during the middle transition period. In stark contrast, across remaining samples, there is clear variation between the higher order moments for the innovations of both exchange rate returns. In fact, the estimated sample correlation of $\hat{\xi}_1$ and $\hat{\xi}_2$ is -0.0791 for
all samples ending after March 25, 2017. Finally, in terms of notable differences, shocks to CNH returns appear to be much more leptokurtic and sometimes more skewed as well. In fact, for all samples after March 26, 2018, \( \frac{1}{\hat{v}_2} > \frac{1}{\hat{v}_1} \), implying, perhaps, Chinese policy makers have been somewhat successful in avoiding extreme changes in the daily onshore spot rates that are observed in offshore counterparts.

From investigation of the test results in Table 2 and the median of squared values of the asymmetric BEKK model parameters in Table 3, there appears to be evidence of heightened spillovers since August 11, 2015, particularly during the transition period. To assess the possible existence of spillovers more formally, Table 4 provides results for Wald test statistics associated with several hypotheses that relevant coefficients are jointly zero. Again, several findings emerge. First, we note that the transition period is generally associated with the highest degree of spillovers in both the mean and conditional variance equations. Notably, the null hypothesis of joint diagonality for \( A, B, \) and \( D \) is rejected 86.93% of the time for our middle sample. Taken together with the findings above as it relates to \( v_t \) and \( \xi_t \), it seems reasonably clear that these two markets experienced a relatively high degree of integration immediately after the PBoC altered the mechanism via which the central parity rate was set on August 11, 2015. Secondly, it seems clear that CNY shocks and volatilities still exert considerable influence on the conditional variance of CNH disturbances. For example, the null hypothesis of no shock or volatility impact can be tested via restrictions on the row-2 column-1 elements of \( A, B, \) and \( D \). The test that the associated coefficients are zero in these matrices is rejected 67.43% and 59.92% of the time for the last two samples using a 5% test size. Finally, there is compelling evidence of strengthening spillovers from CNH to CNY markets relative to the early subsample. Here, we notice that shock spillovers exhibit an increasing influence, potentially buoyed by strong asymmetry as further
discussed below. Overall, the evidence suggests that volatility spillovers now run largely in both directions.

To shed further light on the underlying volatility relationships, Figure 5 presents the Wald-test statistics for the null of no conditional variance-based spillovers in each direction for all three policy related subsamples. As seen in the graph, the null is most consistently and strongly rejected when considering the impact on CNH returns for the first subsample. The effects appear to be roughly equal during the transition period, while there is now increasing evidence that CNH-based shocks and volatilities impact the onshore market. In fact, while bi-directional feedback is generally found for all samples after May 2019, the test-statistics for no feedback from the CNH to CNY market imply an impact with stronger statistical significance. In general, the obvious spillovers at the end of the sample could also be attributable to events associated with COVID-19.

The more obvious existence of bi-directional spillovers coincides with significantly more evidence of asymmetry in the conditional variance matrix, $H_t$, as analyzed in the final panel of Table 4. Here, the null hypothesis that all elements of the matrix $D$ are jointly 0 is increasingly rejected for all subsamples. Additionally, there is only 1 subsample after November 1, 2018, where we fail to reject the associated hypothesis connected to symmetry in $H_t$. These results support the intuition that unexpected depreciations of the RMB are now expected to exhibit a larger impact than before in an environment where the PBoC now formally supports two-way fluctuation in the RMB. Existing studies that impose symmetry on the conditional variance matrix of RMB-based returns will likely generate potentially distorted measures of volatilities rendering subsequent analysis problematic.\footnote{In a GARCH-in-mean context, Smallwood (2021) shows that the consequences of ignoring existing asymmetry in BEKK models can be quite severe, while modelling non-existent asymmetry is substantially less problematic.} Perhaps most importantly, we see that time-varying
existence of asymmetry also impacts the extent to which shock spillovers dominate in one market versus the other. Most notably, the strongest evidence supporting shock spillovers from onshore to offshore markets is observed during the transition period. In contrast, for the most recent samples, the statistical evidence is generally strongest when analyzing the impact of CNH shocks on CNY volatilities. Here, the hypothesis associated with a lack of shock spillovers is rejected for 53.26% of the samples, whereas CNY shocks are only found to have a statistically significant impact on CNH-based volatilities 49.09% of the time.

Overall, the findings in this section point to the prevalence of bi-directional volatility feedback, particularly in recent samples where evidence of asymmetry is extremely strong. At the same time, it seems that the departures from normality are most dramatic for CNH returns. To further isolate the specific impacts of unexpected RMB weakness relative more completely to strength, additional tools are needed. We therefore consider volatility impulse response analysis in the next section.

5. Impulse response analysis

To shed further light on the relationships between CNY and CNH exchange rates and their associated volatilities, this section considers impulse response analysis. Given the highly non-linear relationships, particularly in volatilities, we employ extensive simulations based on the generalized impulse response methodology pioneered by Koop et al. (1996). The associated tools can also be used to generate volatility impulse response functions (VIRF) as initially studied by Hafner and Herwartz (2006) and Shields et al. (2005). To gain an understanding of the relevance of shocks from one market to the other, we use the generalized forecast error variance decomposition proposed by Lanne and Nyburg (2016) to calculate several spillover indices following Diebold and Yilmaz (2012).
We begin with a discussion of the precise methods used to construct our impulse response measures. Koop et al. (1996) define the GIRF as the difference between two conditional \( n \)-step ahead forecasts for an initial history. The analysis has been extended to analyze the impact of shocks on the conditional variance matrix yielding a volatility impulse response function (VIRF). Given that our interest primarily centers on volatility spillovers, we closely follow Shields et al. (2005) and Green et al. (2018) to construct our VIRF, where a measure of the impulse response for mean equation variables is constructed as a by-product.

For the volatility impulse response function, let \( Q_t = \text{vech}(H_t) \), where \( \text{vech} \) is the half vectorization operator that stacks the lower triangular elements of \( H_t \). Hafner and Herwartz define the volatility impulse response function at horizon \( n \) as,

\[
\text{VIRF}(n, V_t, \Omega_{t-1}) = E[Q_{t+n} | Z_t, \Omega_{t-1}] - E[Q_{t+n} | \Omega_{t-1}],
\]

where \( Z_t \) is a random 2x1 vector of shocks, and \( \Omega_{t-1} \) is the information set at time \( t-1 \). As in Koop et al. (1996) and Hafner and Herwartz (2006), the associated impulse response functions can condition on a particular shock vector, \( z_t = \delta \), and history \( \omega_{t-1} \), yielding the VIRF defined as,

\[
\text{VIRF}(n, V_t, \Omega_{t-1}) = E[Q_{t+n} | z_t = \delta, \omega_{t-1}] - E[Q_{t+n} | \omega_{t-1}].
\]

The associated measure in (8) can be interpreted as a realization of the random variable in (7) and easily applied to also calculate the generalized impulse response function. We are specifically interested in extreme shocks to news, associated with the independent innovation \( z_t \) defined in equation (8). Here, we describe the algorithm where the empirical distribution is used to draw shocks, although we also considered a baseline case as described below where shocks are based on twice the standard deviation of the relevant value of \( z_t \). Here, we calculate both a sequence of GIRFs and VIRFs for each of the 2182 subsamples using the following steps, which each consist of 239 observations given \( P=1 \).
i. For each subsample, from the estimated conditional variance matrices ($\tilde{H}_t$) and
associated residuals ($\tilde{\epsilon}_t$), retrieve the news vector as $\tilde{z}_t = \tilde{\epsilon}_t \tilde{H}_t^{-1/2}$.

ii. For CNY-based returns, large negative ($\delta_{CNY^{-}}$) and positive shocks ($\delta_{CNY^{+}}$) are
obtained from the 1% and 99% quantiles of $\tilde{z}_t$. Shocks for CNH-based returns are
analogously obtained. These shocks are fixed for each subsample.

iii. Within a given subsample at time-\(t\), we condition on each available history, $\omega_{t-1}$. At
each history, we randomly sample with replacement from all elements of $\tilde{z}_t$ to obtain
\(n+1\) bootstrapped innovations, $\{z_{t+h}^{*}\}$, $h=0,\ldots,n$. A second set of innovations is
obtained that is identical to these, except that the desired element of $z_{t+h}^{*}$ is replaced
with the desired shock from step (ii). Denote these innovations as $\{z_{t+h}^{*\delta}\}$.

iv. As in Shields et al. (2005) and Green et al. (2018), the time-varying contemporaneous
dependence is returned to the innovations in step (iii). In particular, $\epsilon_{t+h}^{*} = z_{t+h}^{*} \tilde{H}_{t+h}^{1/2}$,
with analogous meaning for $\epsilon_{t+h}^{*\delta}$. These bootstrapped errors will also be used to
generate the GIRF using similar steps that follow.

v. The bootstrapped errors in step (iv) are used to generate two forecasts for the
conditional variance matrices using estimated parameters from the mean equation and
asymmetric BEKK models in equation (2). The difference between these two-
forecasted values yields the $n+1$ values of the VIRF in equation (8).

vi. For each history, $\omega_{t-1}$, the procedure in steps (iii)-(v) is repeated $\bar{R}$ times. The
average over all $\bar{R}$ simulations yields the estimated volatility impulse response
function (and associated GIRF) at time $t$. Throughout, we set $\bar{R} = 500$.

---

12 Following Green et al. (2018), we use the actual estimated conditional variance matrices for each forecasted time period.
Coupled with the effect of lagging, where we start with the third available observation, there are 213 available histories to iterate
on within each subsample.
vii. We update the history to obtain $\omega_t$ and repeat steps (iii)-(vi) to calculate the estimated impulse response functions for time-period $t+1$.

viii. The procedures in steps (iii)-(vii) is repeated until the end of the sample is reached. Following Green et al. (2018), we use the average of all days in each subsample as our final measures of the associated impulse response functions.

For both the GIRF and VIRF, the analysis yields a set of 2182 separate generalized and volatility impulse response functions for horizons up to 24. It is necessary to present summary statistics that provide information related to the bidirectional feedback between CNY and CNH returns and their associated volatilities. In this case, we use total and directional spillovers as studied by Diebold and Yilmaz (2012) based on the generalized forecast error variance decompositions of Lanne and Nyberg (2016). Here, $\lambda_{ij,\omega_{t-1}}(h)$ is the relevant statistic that measures the contribution of a shock to the $j$-th variable on variable-$i$, relative to shocks to both variables. Let GIRF$(h, \delta_j l, \omega_{t-1})_l$ denote the GIRF for the $i$-th variable given a shock of size $\delta_j l$ to the $j$-th variable for a horizon $h$ and a given history $\omega_{t-1}$. Then, $\lambda_{ij,\omega_{t-1}}(h)$ is defined as,

$$
\lambda_{ij,\omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(l, \delta_j l, \omega_{t-1})_l^2}{\sum_{j=1}^{2} \sum_{l=0}^{h} GIRF(l, \delta_j l, \omega_{t-1})_l^2} i, j = 1, 2.
$$

(9)

The denominator measures the aggregate cumulative effect of all the shocks, whereas the numerator is the cumulative effect of the $j$-th shock. Suppressing notation for the history and horizon, which we set to 24, $\lambda_{12}$ denotes the contribution of shocks to CNH returns on CNY returns, while $\lambda_{21}$ captures the reverse. Entirely analogous quantities can be calculated when analyzing the VIRFs.

To capture total spillovers for the $k$-th subsample, the statistic $TOTAL_k=0.5(\lambda_{12}^{(k)} + \lambda_{21}^{(k)})$ is used. $TOTAL_k$ measures the proportion of all shocks that are attributable to spillover impacts.
excluding the own equation effects. Similarly, to determine which market dominates spillover
effects, we analyze the statistic $\text{NET}_k = 0.5(\lambda_{12}^{(k)} - \lambda_{21}^{(k)})$. If $\text{NET}_k > 0$, this implies off-shore markets
have a relatively large spillover impact, whereas negative values imply the relative dominance of
CNY-based returns and volatilities.

Throughout, we concentrate more on the volatility impulse response analysis, given the
novelty of our approach to volatility spillovers for CNH and CNY returns. Consider first Figure
6, which provides the median VIRF across each of our three identified policy subsamples. On the
left-hand side of the Figure, we report impacts associated with shocks to CNY returns, with the
effects of CNH-based counterparts appearing on the right-hand side. We consider the median
VIRFs for both positive and negative shocks, considering here a baseline case. Specifically, with
$\delta_{c_{\text{CNY}}}$ denoting the standard deviation of the independent innovations for CNY returns, $\delta_{c_{\text{CNY}}^+} =
2\delta_{c_{\text{CNY}}^-}$ and $\delta_{c_{\text{CNY}}^-} = -\delta_{c_{\text{CNY}}^+}$. Analogous meaning is ascribed to $\delta_{c_{\text{CNH}}^+}$ and $\delta_{c_{\text{CNH}}^-}$.

Figure 6 documents the importance of asymmetry and its evolving role in capturing the
dynamics of RMB volatilities. Although the conditional variance is generally expected to
increase more with negative shocks given the quadratic nature of the BEKK model parameters,
the magnitude of the increase is quite surprising in several cases. The impact of asymmetry is
perhaps most important in the recent data. As seen in the last panel, for example, a negative
CNY-based shock increases the conditional variance of CNH innovations by even more than it
does its own conditional variance. Perhaps even more importantly, for the final plot on the right-
hand side, we see that the estimated effect of a positive CNH-shock on the CNY-based volatility
is essentially zero. The same shock only causes a modest increase in the conditional variance of
CNH disturbances. In sharp contrast, there are large increases in the volatilities of both variables
associated with an unexpected CNH depreciation. For the most recent period, the implications
are that unexpected RMB depreciations cause market participants to react more, while taking corresponding appreciations in stride. Of particular importance, studies that ignore asymmetry in the conditional variance matrix will likely obtain a distorted measure of the associated volatilities. In these cases, the volatilities are derived under the assumption that RMB appreciations and depreciations have a somewhat symmetric impact, and this limits the ability of the researcher to fully measure differential impacts of positive and negative shocks. Subsequent analyses using these volatilities may be suspect as well.

In Table 5, we now more formally investigate the extent to which spillovers are relevant using the statistics of Diebold and Yilmaz (2012), as discussed above. In the top panel, we report findings associated with the mean equations, providing there the summary statistics for the baseline case. Reinforcing the findings from Table 4, we see that CNH shocks dominate in terms of mean equation effects. For the most recent subsamples, the $NET$ statistic indicates that when cross-equation impacts materialize, roughly 93% are attributable to the effect of CNH returns on those of CNY. Even still, it is important to realize that the overall impacts are somewhat small. First, even in the most recent subsample, the median of $NET$ is only 4%, and cross-equation impacts overall appear to be somewhat modest with a value for $TOTAL$ equivalent to about 27%. Nonetheless, the findings demonstrate that during the most recent period characterized by internationalization and a more market-oriented onshore rate, short-run mean equation spillover effects now run largely in one direction.

The primary findings in Table 5 are reported in the bottom panel, where we provide several statistics associated with the VIRFs. Here, we include a variety of directional statistics for both the baseline case and for the case where shocks are drawn from the potentially skewed empirical distributions. Several important findings emerge that are likely to prove important for
researchers and policy makers. We first see that asymmetry is quite important. Under positive shocks, or unexpected appreciations of the RMB, the onshore market still dominates spillovers. Except for the most recent subsample where shocks are drawn from the skewed empirical distribution, the NET statistics are more often less than 0, indicating a stronger spillover from CNY to CNH than the reverse. In stark contrast, under negative shocks, the proportion of positive values for NET increases for all subsamples and exceeds 66% in the most recent data regardless of how shocks are drawn. Furthermore, the stronger cross-equation impact of CNH volatilities appears to be strengthening. To demonstrate this point, consider Figure 7, which provides a plot of the NET statistic since July 2019 for the baseline case under a negative shock. Notably, there appears to be substantial persistence in positive values of NET as seen from October 2019 through February 2019 and for every observation after May 14, 2020. Additionally, we see that for the last subsample, the median value of NET tends to be quite large, particularly when shocks are drawn from the empirical distribution. Here, with the median value of NET equal to 30.13%, we see that CNH dominates volatility spillovers when negative shocks are drawn from a potentially non-Gaussian empirical distribution possessing non-zero skew. Overall, the evidence shows that the composition of spillovers is dependent on the type of shock. For unexpected depreciations (positive shocks), spillovers appear to still largely run from CNY to CNH, although there can be exceptions. Perhaps more importantly, however, as it specifically relates to the most recent sample, unexpected RMB depreciations will generate a substantially heightened relative impact of CNH shocks on CNY volatilities. The evidence clearly seems to show that negative shocks elevate the importance of offshore markets in generating spillovers.

Finally, we see that across all subsamples and types of shocks, the TOTAL statistic is higher for the conditional variance than it was for the mean equation. In general, TOTAL is
greater than 40%, implying that cross-equation impacts are responsible for close to half of all shock responses. As evidenced by the conditional variance, the degree of integration between these two markets seems to be quite high.

6. Conclusion

The manuscript adds new insight into the relationship between the evolving onshore and offshore RMB markets by combining an asymmetric BEKK model with arguably the most general distributional assumptions for innovations used to date. For a full set of rolling subsamples, computed volatility impulse response functions allow us to more completely quantify the impact of negative shocks associated with unexpected RMB weakness. For the most recent data, the results show that departures from normality are most dramatic for CNH returns, suggesting that policy makers within China may be using existing price discovery to smooth exchange rate changes in the onshore market. At the same time, bi-directional volatility spillovers exist, where very strong evidence of asymmetry suggests onshore markets are more susceptible to external shocks under an RMB depreciation. Under two-way fluctuations and increasing internationalization of the RMB, the implications are that policy makers should be mindful of external shocks that can lead to internal instability, particularly as the RMB weakens unexpectedly in offshore markets.

Our findings also have implications for other studies implementing GARCH-based methods. Our results clearly indicate that asymmetric dynamics in the conditional variance matrix can have vital implications for the impact of shocks. The consequences of ignoring asymmetry may produce distorted measures of volatility and impact the ability to differentiate between the effects of an unexpectedly strong asset relative to a weak one. Finally, our volatility impulse response methods show that impact of shocks can differ substantially when the
underlying distributions are skewed. Overall, we feel that researchers may want to carefully consider deviations from normality with more flexible distributional assumptions, even in instances where quasi maximum likelihood is implemented.

References


Table 1

Descriptive statistics

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<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
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Full Sample: August 24, 2010 through July 17, 2020

<table>
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<th>Obs</th>
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<th>Std. Dev.</th>
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Subsample: August 24, 2010 through August 10, 2015

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Subsample: August 11, 2015 through May 25, 2017

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Subsample: May 26, 2017 through July 17, 2020

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Notes: The common sample runs from August 24, 2010 through July 17, 2020. $s_t^{CNY}$ denotes the original dollar price of the CNY exchange rate, with similar meaning for the CNH rate as it relates to $s_t^{CNH}$. CNY and CNH returns ($r_t^{CNY}$ and $r_t^{CNH}$) are calculated as 100 multiplied by the log difference of the original rates. Time periods for relevant subsamples are shown in headers.
Table 2
Proportion of significant coefficients for identified policy periods

Mean equation: $\Delta Y_t = c + \Phi_1 \Delta Y_{t-1} + \Lambda(s^C_{t-1} - s^C_{t-1}^{CNH}) + \epsilon_t$

<table>
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<tr>
<th>Coefficient Vector/Matrix</th>
<th>Pre-811 Period</th>
<th>Transition Period</th>
<th>CCF Period</th>
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<td>$\lambda_1$</td>
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<tr>
<td><strong>$\Phi_1$</strong></td>
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<td>0.0229</td>
<td>0.0113</td>
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Variance equation:

$$H_t = CC' + A\epsilon_{t-1}e'_{t-1} + BH_{t-1}B' + D\xi_{t-1}\xi'_{t-1}D'$$

<table>
<thead>
<tr>
<th>Coefficient Vector/Matrix</th>
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<th>Transition Period</th>
<th>CCF Period</th>
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<td>0.3899</td>
<td>0.2010</td>
</tr>
<tr>
<td>CNY → CNH</td>
<td>0.4612</td>
<td>0.5573</td>
<td>0.3460</td>
</tr>
<tr>
<td>CNH → CNH</td>
<td>0.4306</td>
<td>0.4312</td>
<td>0.4086</td>
</tr>
<tr>
<td><strong>$B$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY → CNY</td>
<td>0.9082</td>
<td>0.6147</td>
<td>0.5000</td>
</tr>
<tr>
<td>CNH → CNY</td>
<td>0.1827</td>
<td>0.3761</td>
<td>0.2258</td>
</tr>
<tr>
<td>CNY → CNH</td>
<td>0.1786</td>
<td>0.4541</td>
<td>0.2977</td>
</tr>
<tr>
<td>CNH → CNH</td>
<td>0.9112</td>
<td>0.9335</td>
<td>0.7702</td>
</tr>
<tr>
<td><strong>$D$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY → CNY</td>
<td>0.1653</td>
<td>0.1032</td>
<td>0.2755</td>
</tr>
<tr>
<td>CNH → CNY</td>
<td>0.1071</td>
<td>0.1101</td>
<td>0.3864</td>
</tr>
<tr>
<td>CNY → CNH</td>
<td>0.0296</td>
<td>0.2064</td>
<td>0.2546</td>
</tr>
<tr>
<td>CNH → CNH</td>
<td>0.2327</td>
<td>0.2638</td>
<td>0.2833</td>
</tr>
</tbody>
</table>

Notes: Pre-811 refers to results for all subsamples ending prior to August 11, 2015, while CCF-period refers to samples ending after May 25, 2017. The transition period results refer to those from samples between August 11, 2015 and May 24, 2017. For every eligible subsample, the Table reports the proportion of results where the hypothesis that an individual coefficient is zero (or 1 in the case of the skew parameters) is rejected using t-statistics based on numerical standard errors and a 5% test-size. For example, for the coefficient matrix $D$, CNH → CNY reports results associated with the row-1 column-2 element of $D$, connected to the hypothesis of no asymmetric spillover from CNH to CNY markets.
### Table 3

**Median Parameter Values**

Mean equation: \( \Delta Y_t = c + \Phi_1 \Delta Y_{t-1} + \Lambda (s_{t-1}^{CNY} - s_{t-1}^{CNH}) + \varepsilon_t \)

<table>
<thead>
<tr>
<th>Coefficient Vector/Matrix</th>
<th>Pre-811 Period</th>
<th>Transition Period</th>
<th>CCF Period</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MEAN EQUATION PARAMETERS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Lambda )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \lambda_1 ) (CNY)</td>
<td>0.0049</td>
<td>-0.0432</td>
<td>-0.2205</td>
</tr>
<tr>
<td>( \lambda_2 ) (CNH)</td>
<td>0.1236</td>
<td>0.1090</td>
<td>0.1823</td>
</tr>
<tr>
<td>( \Phi_1 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNY</td>
<td>-0.1841</td>
<td>-0.1587</td>
<td>-0.1746</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNY</td>
<td>0.1353</td>
<td>0.1732</td>
<td>0.1569</td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNH</td>
<td>0.0594</td>
<td>0.0483</td>
<td>0.0585</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNH</td>
<td>-0.0680</td>
<td>-0.0214</td>
<td>-0.0210</td>
</tr>
</tbody>
</table>

Variance equation: 

\( H_t = C\varepsilon_t' + A\varepsilon_{t-1}\varepsilon_{t-1}' + BH_{t-1}B' + D\Xi_{t-1}\Xi_{t-1}'D' \)

<table>
<thead>
<tr>
<th>Coefficient Vector/Matrix</th>
<th>Pre-811 Period</th>
<th>Transition Period</th>
<th>CCF Period</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ARCH</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( A ) ( (a^2_{i,j}) )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNY</td>
<td>0.1726</td>
<td>0.3857</td>
<td>0.1267</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNY</td>
<td>0.0075</td>
<td>0.0541</td>
<td>0.0380</td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNH</td>
<td>0.1283</td>
<td>1.1336</td>
<td>0.2636</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNH</td>
<td>0.0642</td>
<td>0.2706</td>
<td>0.2089</td>
</tr>
<tr>
<td><strong>GARCH</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( B ) ( (b^2_{i,j}) )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNY</td>
<td>0.5569</td>
<td>0.5144</td>
<td>0.4789</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNY</td>
<td>0.0144</td>
<td>0.0233</td>
<td>0.0641</td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNH</td>
<td>0.0262</td>
<td>0.6093</td>
<td>0.1630</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNH</td>
<td>0.6063</td>
<td>0.8315</td>
<td>0.7753</td>
</tr>
<tr>
<td><strong>ASYMMETRIC COEFFICIENTS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( D ) ( (d^2_{i,j}) )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNY</td>
<td>0.0348</td>
<td>0.1923</td>
<td>0.1423</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNY</td>
<td>0.0076</td>
<td>0.0365</td>
<td>0.2535</td>
</tr>
<tr>
<td>CNY ( \rightarrow ) CNH</td>
<td>0.0721</td>
<td>0.5036</td>
<td>0.2003</td>
</tr>
<tr>
<td>CNH ( \rightarrow ) CNH</td>
<td>0.0975</td>
<td>0.3154</td>
<td>0.2646</td>
</tr>
<tr>
<td>Skew Parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY</td>
<td>1.1000</td>
<td>1.0633</td>
<td>1.0739</td>
</tr>
<tr>
<td>CNH</td>
<td>0.8566</td>
<td>1.1030</td>
<td>1.0914</td>
</tr>
<tr>
<td><strong>Degree of Freedom Parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Values of ( v = (v_1, v_2) )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY</td>
<td>4.4271</td>
<td>2.7890</td>
<td>7.7440</td>
</tr>
<tr>
<td>CNH</td>
<td>4.9909</td>
<td>3.0787</td>
<td>4.0985</td>
</tr>
</tbody>
</table>

Notes: The Table provides the median value for all parameters in each subsample, except for BEKK model parameters. Here, for elements of the matrices \( A, B, \) and \( D, \) we report the median of the squared values given the quadratic nature of the model. See Table 3 for additional details about the various subsamples and parameter interpretation.
Table 4
Joint Parameter Hypotheses

<table>
<thead>
<tr>
<th>Restriction</th>
<th>Pre-811 Period</th>
<th>Transition Period</th>
<th>CCF Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \phi_{1,2} = \phi_{2,1} = 0 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Spillover</td>
<td>0.6939</td>
<td>0.8578</td>
<td>0.4426</td>
</tr>
<tr>
<td>Either Way</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Mean equation:
\[
\Delta Y_t = c + \Phi_1 \Delta Y_{t-1} + \Lambda (s_{t-1}^{CNY} - s_{t-1}^{CNH}) + \epsilon_t
\]

Restriction

Pre-811 Period Transition Period CCF Period

Variance equation:
\[
H_t = C'C + A \epsilon_{t-1} \epsilon_{t-1}' A' + BH_{t-1} B' + D \Xi_{t-1} \Xi_{t-1}' D'
\]

Variance equation: NO SHOCK SPILLOVER

| a_{i,j}, d_{i,j} = 0 | CNH → CNY | 0.1980 | 0.3922 | 0.5326 |
| a_{i,j}, d_{i,j} = 0 | CNY → CNH | 0.4469 | 0.5642 | 0.4909 |

Variance equation: NO SHOCK OR VOL. SPILLOVER

| a_{i,j}, d_{i,j} = 0 | CNH → CNY | 0.2663 | 0.6078 | 0.5744 |
| a_{i,j}, d_{i,j} = 0 | CNY → CNH | 0.4235 | 0.6743 | 0.5992 |
| a_{i,j}, d_{i,j} = 0 | NO        | 0.5500 | 0.8693 | 0.8003 |
| all i ≠ j          | SPILLOVER |       |        |        |

Variance equation: NO ASYMMETRY

| D=0 | No asymmetry | 0.5316 | 0.5734 | 0.8133 |

Notes: For every eligible subsample, the Table reports the proportion of results where the joint hypothesis that a set of coefficients is zero is rejected using Wald test statistics based on the numerical information matrix and a 5% test-size. Results for spillover effects in the mean equation are reported in the top panel, whereas the panels at the bottom report findings related to the conditional variance matrix. A lack of shock spillovers can be tested via hypotheses related to off-diagonal elements in \( A \) and \( D \), while restrictions on \( A, B, \) and \( D \) can be implemented to test the null of no shock or volatility spillovers. For example, if the row-1, column-2 elements of \( A, B, \) and \( D \) are all zero, there is no spillover from CNH-based volatilities to the conditional variance of innovations for CNY returns. In the last panel, asymmetry in the conditional variance matrix can be test by means of a Wald test associated with the 4 restrictions that all elements in \( D \) are jointly zero. Please see Tables 1 and 2 for more detail on the relevant subsamples.
Table 5
GIRF and VIRF analyses

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean Equation Effects: Positive 2-std deviation shock</th>
<th>Variance Equation Effects: Positive 2-std deviation shock</th>
<th>Variance Equation Effects: Extreme positive shock (99% from empirical distribution of $z_t$)</th>
<th>Variance Equation Effects: Extreme negative shock (1% from empirical distribution of $z_t$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Subsample</td>
<td>Subsample</td>
<td>Subsample</td>
<td>Subsample</td>
</tr>
<tr>
<td></td>
<td>Pre-811 Period</td>
<td>Transition Period</td>
<td>CCF Period</td>
<td>Pre-811 Period</td>
</tr>
<tr>
<td>Prop. of $NET_k&gt;0$</td>
<td>0.4888</td>
<td>0.6913</td>
<td>0.9308</td>
<td>0.4378</td>
</tr>
<tr>
<td>Median $NET_k$</td>
<td>-0.0019</td>
<td>0.0437</td>
<td>0.0420</td>
<td>-0.1833</td>
</tr>
<tr>
<td>Median $TOTAL_k$</td>
<td>0.1175</td>
<td>0.2032</td>
<td>0.2663</td>
<td>0.4453</td>
</tr>
</tbody>
</table>

Notes: The Table summarizes statistics related to VIRF and GIRF analysis for each defined subsample. If $NET>0$, then the impact of a CNH-shock on the relevant CNY variable (relative to the impact of all shocks to the CNY variable), is larger than the corresponding impact of a CNY-shock on the corresponding CNH variable. $TOTAL$ lies between 0 and 1 and measures the impact of spillover shocks relative to all shocks. For each subsample, we provide the proportion of NET statistics that are positive, along with the median value for the $NET$ and $TOTAL$ statistics for different shocks. Positive/negative “2-std deviation shocks” are based on twice the standard deviation of $z_t$, whereas shocks are otherwise drawn from the empirical distribution of $z_t$ for every sample. See the discussion in Section 5 for more detail.
Figure 1
CNY and CNH Returns with Rolling Subsamples
Figure 2
Sample Kurtosis and Skewness for All Subsamples
Figure 3
Speed of Adjustment Coefficients for CNY and CNH Returns
Figure 4a
Estimates of $1/\nu_t$ for CNY and CNH Returns

Figure 4b
Estimates of $\xi_t$ for CNY and CNH Returns

Figure 5
Wald Test Statistics for Hypothesis $a_{i,j} = b_{i,j} = d_{i,j} = 0, i \neq j$
Figure 6
Median Volatility Impulse Response Function: All Subsamples
(Dotted lines indicate effects from the conditional variance of the other variable)
Figure 7
Value of $NET$ for negative (symmetric) shocks since July 2019