# The evolution of the relationship between onshore and offshore RMB markets under asymmetric volatility spillovers

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**Abstract:**
The exchange rate system in China is unique, where onshore and offshore markets exist for a single currency. This paper investigates the evolution of information transmission for each market and explores their relative roles in driving price discovery and volatility spillovers as the RMB becomes more market oriented. We find that onshore returns and volatilities are increasingly influenced by the offshore market, with differences across various exchange rate policy phases. Using a novel method to capture asymmetric spillovers, the findings also show that the volatility of the onshore market is much more susceptible to offshore shocks when the RMB depreciates. To determine the factors influencing the strength of volatility spillovers, we provide additional regression analysis. The results show that capital flows and the degree of intervention are important determinants of information flows under unexpected RMB weakness in recent samples.

**Keywords:** Onshore and offshore RMB spillovers, asymmetric BEKK, multivariate skew-Student density function

**JEL Codes**: F31, F33, C32

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# I. Introduction

There are few events in international finance over the past two decades that have been more remarkable than the ascendancy of the renminbi (RMB) on the global stage. Internationalization has been accomplished through the establishment of satellite markets in offshore centers rather than through liberalization of the capital account. The co-existence of two currency markets, with onshore and offshore exchange rates referred to as CNY and CNH, provides opportunities to officials to test-pilot programs and expand the use of China's currency, while avoiding the consequences of too quickly liberalizing capital flows in a domestic financial market that has not fully matured. However, challenges exist if speculation could be channeled onshore, especially if the offshore market dominated information flows. As liberalization accelerates, spillovers into China can create unsettling exposure to international financial risk, threatening RMB stability. In the opposite direction, impacts flowing from the mainland could convey information to the global economy as the exchange rate system in China evolves. More generally, spillovers provide crucial information that can be used by currency traders and policy makers in understanding price discovery and assessing new risks (see Ross, 1989 and Hong, 2001).

The special case of segmentation of two markets for one currency has attracted growing academic attention, yielding a new flourishing research area. There have been a small number of studies focusing specifically on return differentials (Funke et al., 2015, Liang et al., 2019, and Sun et al., 2020), and a larger literature has studied information transmission between the two markets. In terms of the latter line, several studies concentrate on the state of return and volatility spillovers (see Maziad and Kang, 2012, Cheung and Rime, 2014, Ding et al., 2014, Ho, Shi, and Zhang, 2018, and Hu et al., 2023). Other studies have analyzed the impact of specific economic events or changes in policy. For example, Chen and Xu (2021) explore the impact of the inclusion of the RMB in the IMF's special drawing rights basket, while several studies specifically analyze the effect of the milestone exchange rate reform on August 11, 2015 (see, for example, Chen 2020, Li et al. 2021, and Xu et al., 2021). Within the literature, a consensus has emerged that spillovers exist and are time varying (see, for example, Xu et al., 2017, Wan et al., 2020, Zhao et al., 2021 and Tian et al., 2023).

Although research has shown that the relationship between the two markets has changed over time, few studies explore the evolution of the relative strength of each market in information flows. Existing research has also not addressed what factors drive volatility spillovers. We contribute to the existing literature by specifically exploring how and why the strength of the relationship between the two markets has changed. We are motivated by the fact that exchange rate policy within China has continually shifted, with a general move to a more flexible currency. Trading bands for CNY rates have gradually widened and there have been additional reforms associated with establishing a more market based central parity rate (see, Das, 2019). While the onshore exchange rate system has changed, the offshore market has also grown in importance and is likely populated with heterogenous traders, some of which are more sophisticated compared to relatively uninformed agents. In this environment, asymmetric herding and enhanced volatility can occur under negative shocks when uninformed traders mimic the behavior of leading agents in offshore markets as official support is withdrawn (see Park, 2011).

The continual evolution of exchange rate policy within China and emergence of the offshore market calls for study of the dynamics of the intermarket information spillovers between the two markets. International investors are certain to monitor changes to PBoC policy in forming expectations regarding the RMB. When officials are heavily involved, traders in the offshore market are more likely to receive and process information from the mainland. However, during periods when intervention falls, information embedded in onshore rates declines, and a potential vacuum is created.  This is particularly true as market forces have historically been less responsible for movements in the onshore rate. The void can be filled by offshore centers, where trade occurs in unregulated markets, allowing the RMB to quickly reflect global changes in demand and supply (see, Funke et al., 2022).

Considering the unique environment for the RMB and the continual evolution of the two trading centers for the currency, several important questions emerge. First, how has the relative importance of each market changed across different exchange rate policy phases as the RMB transitions toward a more flexible, market-oriented currency? Are there any general patterns that can be observed in the evolving relative roles of CNY and CNH rates in price discovery and information flows? In analyzing information flows through volatility spillovers, do we observe that the offshore market is more likely to dominate under RMB weakness as the PBoC withdraws support? And finally, what factors drive the strength of volatility spillovers from one market to the other, under both RMB weakness and strength?

An understanding of the importance of each market has vital implications for traders and policy makers. Recently, exchange rate management in China has been described by Jermann et al. (2022) as a two-pillar policy, with officials aiming to balance exchange rate flexibility with a currency relative to those of major trading partners that is more generally stable. An investigation of the evolution of the relative strength of each market, along with an understanding of the factors that impact volatility spillovers reveals the potential risk with establishing a link between the onshore and offshore. It can also provide information on the relationship between RMB flexibility and overall stability, which has obvious implications for exchange rate management. The use of a parallel offshore market for internationalization is unprecedented, providing a learning opportunity for other countries where there is little empirical or theoretical guidance. An understanding of the evolutionary features of the intermarket relationships, particularly under currency weakness, could allow authorities to foresee and assess the consequence of "one currency, two markets." Policy makers are especially keen to understand how the onshore exchange rate will be impacted by shocks from international markets under capital account liberalization and a more flexible currency.

In this paper, we provide a comprehensive empirical analysis of the evolution of information and volatility spillovers between onshore and offshore spot RMB markets. To accommodate shifting policies and economic conditions, we use rolling samples of 250 daily observations. Our approach uses a system with the asymmetric BEKK model of Grier at al. (2004) applied to all subsamples. Given evidence of time varying kurtosis and skew in our data, we use the multivariate skew-Student density function introduced by Bauwens and Laurent (2005). We further test for breaks in the variance using the modified iterative cumulative sum of squares methods pioneered by Inclan and Tiao (1994) and Sansó et al. (2004). Based on these tests and changes in policy in China, most notably the August 11, 2015 exchange rate reform (hereafter "8-11 reform"), we identify four distinct periods.[1] We compute volatility impulse response functions (VIRFs) to isolate volatility spillover dynamics under both unexpected RMB strength and weakness. The associated VIRFs are used to calculate directional statistics based on the analysis of Diebold and Yilmaz (2012), which allows us to quantify both the relative strength of each market and to analyze the factors driving volatility spillovers.

[1] The use of subsample analysis allows us to study the evolution of spillover dynamics and is also vital to ensure robust conclusions. For example, Caporin and Malik (2020) show that the existence of time varying parameters and breaks in the conditional variance of financial assets can induce evidence of spurious volatility transmission.

Our primary findings can be summarized as follows. We provide compelling evidence that during periods when the exchange rate policy in China matures, offshore markets dominate the dynamics of the Chinese currency. Whereas evidence from earlier subsamples demonstrates that CNY returns are weakly exogenous, results for more recent periods show that the onshore market is much more likely to respond to disequilibria. Evidence also shows that when short-run mean equation and volatility spillovers exist, information flows are now substantially more likely to run from offshore to onshore markets. We further find that asymmetry has become a vital feature of volatility dynamics. For example, for the last policy period considered in our sample, the offshore market dominates spillovers with near unanimity under unexpected RMB weakness. The results suggest onshore investors have increasingly followed offshore investors in RMB pricing at the time PBoC support is being withdrawn. Finally, we find that increased capital flows and a decline in official intervention are important factors driving information flows from the offshore to onshore market under unexpected RMB weakness.

Our manuscript provides several important breakthroughs that complement the existing literature. Our paper is one of only a handful of studies that analyzes volatility spillovers between onshore and offshore spot markets and is particularly novel in exploring the evolution of the relationship over a sample that spans numerous policy changes. For example, Maziad and Kang (2012), Liang et al. (2019), Funke et al. (2022), and Hu et al. (2023) estimate multivariate GARCH methods using returns from two markets, sometimes exploring only limited subsamples.[2] Other studies, such as Funke et al. (2015), consider how the conditional variance of

[2] Other studies, including Ho et al. (2018) and Wan et al. (2020) consider the relationship between the volatilities of spot and NDF forward markets, where Wan et al. (2020) include policy dummies in relevant GARCH equations. Neither study explores the time varying nature of the strength of volatility spillovers.

return differentials was influenced by various policy reforms.[3] As discussed above, for studies such as Liang et al. (2019) that employ subsample analysis, a common theme that emerges is that the underlying volatility interactions are likely sample specific. Thus, our use of rolling subsamples will allow to avoid spurious volatility interactions, while also exploring the evolution of the relationships across a variety of policy changes.

Second, we appear to be the first paper to study how RMB depreciations differentially impact the strength of volatility interactions. As discussed above, under asymmetric herding, unexpected currency weakness is expected to impact currency markets differently relative to strength. Additionally, as official support is withdrawn, the epicenter of information regarding RMB dynamics appears to have gradually shifted to the offshore market where potentially more informed agents trade in an unregulated market. In this context, it is worth noting that policy makers see asymmetric herding as an especially relevant issue. For example, according to China's Q2-2017 Monetary Policy Report, "pro-cyclical" herding and "irrational" depreciation expectations create elevated risks that are more likely to appear during episodes of RMB weakness. Anecdotally, episodes illustrating the potential for enhanced spillovers under depreciationary shocks are common.[4]

Third, we use the multivariate skew Student density to model residuals, whereas many studies within the literature use standard inference, despite obvious violations of normality for returns.[5] This innovation is important, since correct modelling of the underlying density is

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[3] To our knowledge, using non-econometric methods for volatility, only Zhao et al. (2021) explores the time-varying nature of the evolution of the strength of onshore and offshore volatility spillovers without statistical tests.
[4] For example, after the China Foreign Exchange Trade System published the currency basket used in setting the daily parity rate in late 2015, traders perceived that it signaled an official intent to weaken the RMB. Subsequently, volatility rose, and the currency continued to weaken into early January 2016, falling more than 2% in one week alone (see, Cheung et al., 2018).
[5] See, for example, Hu et al. (2023), who estimate a multivariate BEKK model under the assumption of Gaussian disturbances and then provide evidence of bilateral spillovers using Wald test statistics. A handful of studies have used a standard Student t-distribution in estimation, including Ho et al. (2017) and Funke et al. (2022).

known to generate estimators that are asymptotically normal and can yield huge efficiency gains relative to the use of QMLE (see, Engle and Gonzalez, 1991). Additionally, more general assumptions allow us to employ impulse response analysis using shocks drawn from empirical distributions with varying kurtosis and skew. Our findings demonstrate that the expected dominance of one market versus the other can depend on how shocks are drawn.

Finally, we study the factors that drive the strength of volatility spillovers, both under unexpected RMB depreciations and appreciations. Several important contributions have shown that variables related to exchange rate reform and economic fundamentals are relevant for RMB differentials and their volatilities.[6] However, we are unaware of any study that seeks to understand the factors that specifically impact why one market dominates spillovers during specific periods. Additionally, we demonstrate that the same variables can impact the volatility relationships differently under unexpected RMB weakness as compared to strength.

The rest of the paper is organized as follows. In Section 2, we provide background information on the unique exchange rate system in China. Section 3 describes the data and provides statistical support for the selected split of our subsamples. Section 4 discusses our methodology, and Section 5 includes our estimation and testing results. Section 6 contains VIRF analysis and discusses the determinants of the relative role of the CNY and CNH exchange rates in volatility spillovers. A final section concludes. An appendix is provided, which describes implemented tests for breaks in the unconditional variance, technical details related to our distributional assumptions, and a thorough description of the algorithms we employ to calculate volatility impulse response functions. The appendix also provides details on data we used for regression analysis associated with volatility spillovers.

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[6] Specifically, Funke et al. (2015), Sun et al. (2020), and Liang et al. (2019) show that variables connected to changes in policy and liquidity can impact return differentials, their intervals, or associated volatilities.

## 2. Background: Two Markets for One Currency

Exchange rate management of the RMB is quite unique, with the existence of parallel markets for the same currency. After the global financial crisis, the introduction of trading in Hong Kong set the stage for internationalization of the RMB and establishment of offshore trading centers. Although full current account convertibility has largely been achieved, China has effectively implemented capital controls that has resulted in two segregated markets for the RMB (see Funke et al., 2015).[7] Both the onshore and offshore markets constitute the pricing of one fiat currency, where each market has unique characteristics. Within the onshore market, an active PBoC can have vital impacts on RMB pricing, although regulation might impact the capacity of the CNY rate to respond to information. In contrast, a major advantage for the offshore market lies in its information efficiency.

Although still regulated, the onshore exchange rate has gradually become more market oriented as RMB internationalization has also started to materialize. The current environment for CNY rates has emerged after continual change in the RMB exchange rate formation mechanism (see, Sun et al., 2020). For example, official 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.[8] Subsequently, the PBoC used the exchange rate reform on August 11, 2015 to eliminate the convention of an opaque setting of the central parity rate in favor of an objective and transparent way to align the exchange rate with market forces. Another major policy

[7] China's capital account has still been ranked among the least open in the world according to the Chinn–Ito index, a widely used indicator for capital account openness (Chinn and Ito, 2006).

[8] Lei et al. (2022) argue that China's exchange rate regime is characterized by evolving *De Facto* bandwidths that are endogenously determined by RMB volatility. After 2017, for example, the authors estimate that bandwidths were reduced to +/- 0.80% against the central parity rate. The authors also show that the size of the bandwidths is negatively correlated with offshore volatility, suggesting policy makers are aware of the potential for spillovers.

occurred on May 25, 2017, when a countercyclical factor (CCF) was introduced. The CCF variable was added to offset perceived herding behavior and overshooting that may have been present when daily rates heavily weighted the previous day's closing price. After the CCF factor was introduced, the modern system for setting the central parity rate has largely been established. The currency still trades within bands of +/- 2% relative to the central parity rate, although regular currency interventions have gradually been withdrawn. Broadly speaking, the onshore rate has been increasingly determined by market forces.

In an aim to internationalize the currency and seed the offshore market, several capital account restrictions have slowly been lifted and cross-border flows have materialized. Offshore settlement began with a small number of currencies in July 2009, and subsequently, cross-border flows via international trade have rapidly developed. Capital account liberalization has been slower due to capital controls, although several policy changes have further contributed to the offshore use of RMB. For example, the RMB qualified foreign and domestic institutional investment programs (RQFII and RQDII) were established in December 2011 and November 2014, and the free trade zone in Shanghai was launched in September 2013.[9]

As a free market, offshore trading centers for the RMB can be used for trade settlement, investment, hedging, and speculative purposes. Here, the currency can be openly traded globally 24 hours a day without capital controls or reference to trading bands and the onshore central parity rate. The CNH rate is determined by market forces, free from direct intervention from the PBoC or entities such as the Hong Kong Monetary Authority.[10] Additionally, offshore centers

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[9] For additional discussion related to changes in Chinese policies impacting capital flows, see Funke et al. (2015), Ito (2017), Liang et al. (2019), and Lai (2021) who provides an outstanding history of offshore development.
[10] Liquidity in the offshore market can be impacted through indirect channels. For example, on Jan. 11, 2016, HIBOR rates spiked after the Bank of China in Hong Kong withheld funding from the market (see, Funke et al., 2022).

are populated with traders that possess experience and knowledge, such that it is not surprising that prior research has found that the CNH rate responds more efficiently to economic and financial shocks (see, Funke et al., 2022). Not surprisingly, the size of the offshore market has gradually grown, where according to the 2022 BIS triennial survey, roughly 78% of RMB transactions occur outside the mainland.

As the management of the RMB has evolved, it seems natural to question how the underlying relationships between the two parallel markets might be impacted. As official onshore support is withdrawn, information flows from the source with the comparative advantage in market pricing. Although efforts are in place to liberalize the RMB, as discussed above, time is needed to allow interbank systems to fully mature. Overall, as China gradually transitions more to a market-based system already in place in offshore markets, we expect the dynamics of the RMB are increasingly determined by CNH rates. Additionally, traders in offshore markets are likely more informed and might be seen as leading agents in the context of the heterogenous agent model of Park (2011). As anecdotal evidence above suggests, herding develops under negative shocks and onshore investors might follow more informed offshore agents. Under RMB internationalization and a more market-oriented onshore rate, the ability for information to flow from offshore centers is enhanced. Therefore, we expect that negative CNH-based shocks associated with unexpected RMB weakness will have a larger impact on CNY volatilities than positive shocks. We further posit that the relative impacts of negative shocks are even stronger during the same periods where the onshore rate is determined more freely.

# 3. Data and Methodology

For our empirical analysis, we use daily closing spot USD prices of the RMB for both markets. Our data begins with the launch of the CNH market on August 23, 2010, ending on July 7, 2023.

After taking log differences of the exchange rates and eliminating data due to holidays and weekends, we have 3144 observations. The log exchange rates of onshore and offshore markets are denoted $s_t^{CNY}$ 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.

One of the aims of this study is to examine how interactions between CNY and CNH markets vary over time as RMB management evolves. The 8-11 reform and introduction of the CCF factor on May 26, 2017 stand out as policy changes meriting special attention. To explore impacts of other policy changes and economic events on the unconditional variance of returns during our sample, we also use the modified version of the iterative cumulative sum of squares (ICSS) method originally developed by Inclan and Tiao (1994). The test is applied to both squared returns and the residuals from a regression of returns on relevant variables.[11] For all tests and for both series, two change points were isolated with dates given by July 30, 2015 and April 18, 2022. The associated test statistics for filtered CNY rates, for example, are given by 2.9931 and 1.6925, with 95% critical values equal to 1.35 in both cases. The first break point corresponds with the 8-11 reform, reinforcing the dramatic impact of this policy initiative, while the second break occurs toward the end of our sample. The results of the structural break tests, along with RMB-based policy changes, allow us to explore the evolution of RMB dynamics grouped into four distinct phases. The associated time periods are labelled “Pre-811” (August 23, 2010-July 31, 2015), “Transition Period” (August 11, 2015 – May 26, 2017), “Two-Pillar Period” (May 27, 2017 – April 18, 2022), and “Post-COVID” (April 19, 2022 – July 7, 2023).

[11] Given the analysis below based on a vector error correction system, residuals are obtained from a regression of each return series on lags of both returns series and an error correction term. Additional details of the tests can be found in the Appendix.

Table 1 provides summary statistics for our data, both for the full sample and the relevant subsamples as discussed above. Results show that unconditional moments are time varying. The earliest subsamples are characterized by a relatively low unconditional standard deviation in both returns series, while later samples are more volatile. Additionally, there is strong evidence of both evolving skewness and kurtosis and differences in these higher order central moments across CNY and CNH returns. Jarque-Bera test statistics, available on request, demonstrate an overwhelming rejection of normality for both returns for virtually every subsample.

# Table 1

Descriptive statistics

| Variable | Obs | Mean | Std. Dev. | Skewness | Kurtosis | Min. | Max. |
|---|---|---|---|---|---|---|---|
| **Full Sample: August 24, 2010 through July 7, 2023** | | | | | | | |
| $s_t^{CNY}$ | 3144 | 0.1529 | 0.0070 | -0.1744 | 1.9330 | 0.1369 | 0.1655 |
| $s_t^{CNH}$ | 3144 | 0.1529 | 0.0070 | -0.1698 | 1.9800 | 0.1362 | 0.1661 |
| $r_t^{CNY}$ | 3144 | -0.0019 | 0.2274 | -0.0101 | 10.2965 | -1.8334 | 1.6070 |
| $r_t^{CNH}$ | 3144 | -0.0023 | 0.2763 | 0.1148 | 11.7223 | -2.6572 | 2.0003 |
| **Subsample: August 24, 2010 through July 30, 2015** | | | | | | | |
| $s_t^{CNY}$ | 1221 | 0.1589 | 0.0042 | -0.8266 | 2.9264 | 0.1468 | 0.1655 |
| $s_t^{CNH}$ | 1221 | 0.1590 | 0.0041 | -0.6684 | 2.7020 | 0.1474 | 0.1661 |
| $r_t^{CNY}$ | 1221 | 0.0074 | 0.1130 | 0.1141 | 6.9500 | -0.5538 | 0.5832 |
| $r_t^{CNH}$ | 1221 | 0.0064 | 0.1589 | -0.0205 | 21.1078 | -1.3214 | 1.6298 |
| **Subsample: August 11, 2015 through May 26, 2017** | | | | | | | |
| $s_t^{CNY}$ | 437 | 0.1507 | 0.0045 | -0.0237 | 1.6566 | 0.1436 | 0.1583 |
| $s_t^{CNH}$ | 437 | 0.1504 | 0.0041 | -0.0085 | 1.7433 | 0.1433 | 0.1582 |
| $r_t^{CNY}$ | 437 | -0.0226 | 0.2177 | -0.8791 | 17.7105 | -1.8334 | 1.1951 |
| $r_t^{CNH}$ | 437 | -0.0212 | 0.3099 | -0.6985 | 17.2609 | -2.6572 | 1.4712 |
| **Subsample: May 31, 2017 through April 18, 2022** | | | | | | | |
| $s_t^{CNY}$ | 1189 | 0.1496 | 0.0057 | -0.0159 | 1.6615 | 0.1393 | 0.1595 |
| $s_t^{CNH}$ | 1189 | 0.1496 | 0.0057 | -0.0215 | 1.6645 | 0.1390 | 0.1599 |
| $r_t^{CNY}$ | 1189 | 0.0062 | 0.2562 | -0.1979 | 6.5544 | -1.5753 | 1.4253 |
| $r_t^{CNH}$ | 1189 | 0.0057 | 0.2921 | 0.0183 | 6.3623 | -1.7436 | 1.4252 |
| **Subsample: April 19, 2022 through July 7, 2023** | | | | | | | |
| $s_t^{CNY}$ | 297 | 0.1448 | 0.0039 | -0.0511 | 2.4613 | 0.1369 | 0.1564 |
| $s_t^{CNH}$ | 297 | 0.1446 | 0.0039 | -0.1220 | 2.4248 | 0.1362 | 0.1558 |
| $r_t^{CNY}$ | 297 | -0.0425 | 0.4000 | 0.6379 | 4.6894 | -1.0010 | 1.6070 |
| $r_t^{CNH}$ | 297 | -0.0422 | 0.4690 | 0.7601 | 5.3431 | -1.3259 | 2.0003 |

*Notes*: $s_t^{CNY}$ and $s_t^{CNH}$ denote the log USD price of the CNY and CNH exchange rates. Returns are denoted $r_t^{CNY}$ and $r_t^{CNH}$. Time periods for relevant subsamples are shown in headers.

In terms of the rolling subsamples, we consider a sequence of 2895 samples, using 250 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 15, 2011. The subsequent subsample uses 250 observations from August 25, 2010 through August 16, 2011, and the procedure continues until the end of the sample is reached.

# 4. Methodology

Here, we describe the methodology for estimation of the model parameters used to measure mean and volatility spillovers. 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 $H_t$ is the conditional variance matrix based on the available information set, $\Omega_{t-1}$. As pre-tests clearly show that original spot rates are non-stationary cointegrated series with unit cointegrating vector, the mean equation model is,

$$\Delta Y_t = c + \sum_{j=1}^{P} \Phi_j \Delta Y_{t-j} + \Lambda (s_{t-1}^{CNY} - s_{t-1}^{CNH}) + \epsilon_t, \qquad (1)$$

where $c$ is a vector of constants, and $\Lambda$ is a 2x1 vector of speed of adjustment parameters. For all subsamples, $P$ is set equal to 1, as this was the value selected by the multivariate Schwarz Bayesian information criteria with near unanimity. Based on equation (1), we can easily distinguish between short and long-run price discovery. If $\lambda_i$ is zero, for example, the associated exchange rate does not respond to disequilibria, yielding weak exogeneity and potential dominance in long-run RMB price discovery. Short-run price discovery is measured by cross-coefficients in $\Phi$ and occurs when the lagged return in one market contains predictive power for returns for the other RMB rate.

To investigate volatility spillovers, we use the asymmetric extension of the BEKK model of Engle and Kroner (1995). The asymmetric BEKK model can be written as,

$$H_t = CC' + A\epsilon_{t-1}\epsilon_{t-1}'A' + BH_{t-1}B' + D\Xi_{t-1}\Xi_{t-1}'D'. \qquad (2)$$

Here, $C$ is a lower triangular 2x2 matrix of constants, $\Xi_t = I_{\{\epsilon_t<0\}} \circ \epsilon_t$, where $I$ denotes the indicator function, and "∘" 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, 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 $\epsilon_t$, as discussed above, most studies analyzing RMB dynamics employ a Gaussian assumption. From Table 1, we see that there is evidence of time varying kurtosis and skew that can differ across CNH and CNY rates. As normality is clearly violated in the data, standard inferential results will be unreliable. As described by Bollerslev and Wooldridge (1992), one option is quasi maximum likelihood estimation (QMLE) and the use of robust standard errors calculated using a sandwich estimator of the variance covariance matrix. Alternatively, as pointed out by Engle and Gonzalez-Rivera (1991), one can attempt to correctly model the density of $\epsilon_t$, rendering maximum likelihood parameter estimates that are asymptotically normal. In this context, parameter standard errors can be consistently estimated using the outer product of the numerical gradient, and conventional inference can be applied, as we do below. Relative to QMLE, Engle and Gonzalez-Rivera (1991) show that efficiency gains from using the correct form of the density can be large when deviations from normality are substantial, as seems obvious for many subsamples here. Further, 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, we employ the multivariate skew-Student density originally studied by Bauwens and Laurent (2005).

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

$$f(z_t) = \frac{4}{\pi}\left[\prod_{i=1}^{2}\frac{\xi_i s_i}{1+\xi_i^2}\frac{\Gamma\left(\frac{\nu_i+1}{2}\right)}{\Gamma\left(\frac{\nu_i}{2}\right)\sqrt{\nu_i-2}}\left(1+\frac{\kappa_{i,t}^2}{\nu_i-2}\right)^{-\frac{1+\nu_i}{2}}\right], \qquad (3)$$

where,

$$\kappa_{i,t} = \left(s_i z_{i,t} + m_i\right)\xi_i^{-I_{i,t}}, \;\; I_{i,t} = \begin{cases} 1\; if \;\; z_{i,t} \geq -\frac{m_i}{s_i} \\ -1\; if \;\; z_{i,t} < -\frac{m_i}{s_i} \end{cases} \qquad (4)$$

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,

$$m_i(\xi_i, \nu_i) = \frac{\Gamma\left(\frac{\nu_i-1}{2}\right)\sqrt{\nu_i-2}}{\sqrt{\pi}\Gamma\left(\frac{\nu_i}{2}\right)}\left(\xi_i - \frac{1}{\xi_i}\right) \qquad (5)$$

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

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.

In our analysis, all parameters are simultaneously estimated.[12] Although multi-step procedures may be expected to yield reliable parameter estimates under normality, 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. 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,

$$log\, L(\theta) = \sum_{t=3}^{T} \{log\, f(z_t) - 0.50|H_t|\}. \tag{6}$$

# 5. Estimation Results

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

*5.1 Price Discovery*

In this section, we discuss the long and short-run price discovery results from the mean equations, concentrating on the four periods that primarily highlight changes in PBoC policy. In the top panel of Table 2, we provide the proportion of times that a given null hypothesis is rejected. Individual tests are associated with the null hypothesis that a given parameter is equal to 0. For the joint hypothesis associated with $\Phi$, we test the null that $\phi_{1,2}$ and $\phi_{2,1}$ are both zero. In the bottom panel of the table, we report associated median parameter estimates.

[12] An iterative method based on a homoskedastic VAR and individual GARCH 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.

## Table 2

Mean Equation Results

| Mean equation: $\Delta Y_t = c + \Phi_1 \Delta Y_{t-1} + \Lambda(s_{t-1}^{CNY} - s_{t-1}^{CNH}) + \epsilon_t$ | | | | | |
|---|---|---|---|---|---|
| Proportion of significant coefficients for identified policy periods | | | | | |
| Coefficients Restriction | | Pre-811 Period | Transition Period | Two-Pillar Period | Post-Covid |
| $\Lambda$ | **MEAN EQUATION: SPEED OF ADJUSTMENT** | | | | |
| | $\lambda_1$ | 0.1111 | 0.3936 | 0.5223 | 0.8889 |
| | $\lambda_2$ | 0.9846 | 0.7368 | 0.4012 | 0.0303 |
| $\Phi_1$ | **MEAN EQUATION: SHORT-RUN IMPACTS** | | | | |
| | CNY → CNY | 0.6389 | 0.5263 | 0.4903 | 0.9461 |
| | CNH → CNY | 0.5658 | 0.7506 | 0.3633 | 0.4747 |
| | CNY → CNH | 0.3045 | 0.1167 | 0.0050 | 0.0067 |
| | CNH → CNH | 0.1502 | 0.0252 | 0.0008 | 0.0000 |
| Joint: $\Phi_1$ | | | | | |
| $\phi_{1,2} = \phi_{2,1} = 0$ | CNH ⇔ CNY | 0.6872 | 0.8604 | 0.5257 | 0.3636 |
| Median Parameter Estimates | | | | | |
| Coefficient Vector/Matrix | | Pre-811 Period | Transition Period | Two-Pillar Period | Post-Covid |
| | **MEAN EQUATION: SPEED OF ADJUSTMENT** | | | | |
| $\Lambda$ | $\lambda_1$ (CNY) | 0.0038 | -0.0402 | -0.2100 | -0.3610 |
| | $\lambda_2$ (CNH) | 0.1254 | 0.1114 | 0.1900 | 0.0757 |
| | **MEAN EQUATION: SHORT-RUN IMPACTS** | | | | |
| $\Phi_1$ | CNY → CNY | -0.1729 | -0.1553 | -0.2353 | -0.3323 |
| | CNH → CNY | 0.1303 | 0.1700 | 0.1652 | 0.2152 |
| | CNY → CNH | 0.0624 | 0.0420 | 0.0419 | -0.1059 |
| | CNH → CNH | -0.0676 | -0.0214 | -0.0397 | 0.0193 |
| **DISTRIBUTIONAL PARAMETERS** | | | | | |
| Skew Parameters | CNY | 1.0947 | 1.0689 | 1.0682 | 1.0213 |
| | CNH | 0.8612 | 1.1099 | 1.0570 | 0.8426 |
| Values of $(\nu_1, \nu_2)$ | CNY | 4.2131 | 2.7463 | 5.5326 | 5.4296 |
| | CNH | 4.9206 | 3.0202 | 4.4696 | 2.9278 |

*Notes*: "Pre-811" refers to results for all subsamples ending prior to Aug. 11, 2015, while "Post COVID" refers to samples ending after April 18, 2022. "Transition Period" results refer to samples between Aug. 11, 2015 and May 26, 2017, with "Two-Pillar" referring to results between May 31, 2017 and April 18, 2022. For every subsample, the table reports the proportion of results where the hypothesis that a coefficient is 0 is rejected using t-statistics based on numerical standard errors and a 5% test-size. For example, for the coefficient matrix $\Phi$, CNH → CNY yields results associated with the row-1 column-2 element of $\Phi$, connected to the hypothesis of no short-run returns spillover from CNH to CNY markets.

As seen in Table 2 above, there is less evidence of short-run bilateral spillovers in recent samples. For example, there is statistically significant evidence of short-run spillovers in at least one direction in 86.04% of our samples during the transition period. In contrast, the same evidence only materializes in 36.36% of the samples after COVID, a finding that can be largely explained by the dynamics in the onshore market. In Table 2, for example, the coefficient associated with short-run spillovers from onshore to offshore markets is only significant 0.50% and 0.67% of the time for findings grouped in our last two subsamples. In contrast, during our last subsample, the coefficient associated with short-run spillovers from the offshore to onshore market is significant 47.47% of the time.

Analysis of the long run dynamics between CNY and CNH returns reveals similar evidence of the strengthening role of offshore markets, after earlier findings showed onshore returns played a leading role in price discovery. Complementing the findings in Table 2, Figure 1 depicts the values of $\hat{\lambda}_i$, where $\hat{\lambda}_1$ hovered near zero for most of the first policy sample, indicating that CNY returns were weakly exogenous. This result is confirmed in Table 2, where prior to August 11, 2015, $\hat{\lambda}_1$ is significant 11.11% of the time. The burden of adjustment clearly falls on CNH returns, where $\hat{\lambda}_2$ is significant at the 5% level with near unanimity.[13] After the introduction of the CCF in 2017, the pattern has completely reversed itself, with a much higher preponderance of significant values of $\hat{\lambda}_1$. As again highlighted in Figure 1, $\hat{\lambda}_1 < 0$ for almost every subsample after the 8-11 reform, while $\hat{\lambda}_2$ has generally been closer to zero, particularly in recent subsamples. The results clearly show that weak exogeneity of CNY markets has been replaced by a leading role of CNH rates in long-run price discovery.

[13] This result is consistent with Cheung and Rime (2014), who also found strong evidence of cointegration between CNH and CNY rates and evidence of weak exogeneity in early samples for CNY returns.

Overall, our investigation of long and short-run price discovery demonstrates that although the relationships are clearly time-varying, the CNH market dominates spillovers after the 8-11 reform as CNY rates have become more market-oriented. Existing research supports our conclusions, as studies provide mixed findings depending on the sample considered. Early research, including Maziad and Kang (2012), Leung and Fu (2014), and Cheung and Rime (2014) generally find that onshore markets dominate return spillovers. While some studies, including Li et al. (2021) and Tian et al. (2023) provide mixed findings for recent samples, others such as Chen (2020), Chen and Xu (2021), and Zhao et al. (2021) generally conclude that the relative role of CNH rates in price discovery has been enhanced.

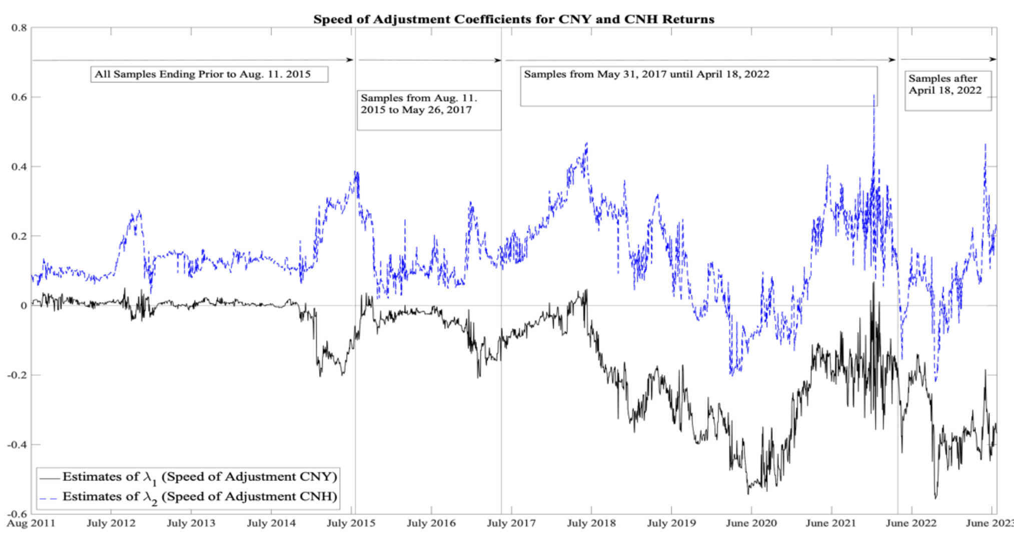


Figure 1: Speed of Adjustment Coefficients for CNY and CNH Returns

Results in Table 2 also provide findings related to distributional parameters that highlight obvious departures from normality and provide strong evidence supporting our distributional assumptions. The findings also yield results that are of independent interest. In general, for the last two subsamples, $\hat{\nu}_1 > \hat{\nu}_2$, implying a lower kurtosis for CNY returns. More granular evidence presented in Appendix A.2 shows that $\hat{\nu}_1$ was generally larger than $\hat{\nu}_2$ for all late subsamples, the exception being the period immediately after COVID. The implications are that Chinese policy makers have been successful in avoiding unpredictable, extreme changes in the daily onshore spot rates that are more common in the offshore market. We also see that the median of the skew parameter for CNH disturbances is substantially less than 1 in our final subsample. This implies that after COVID, unexpected depreciations of offshore RMB were very common. This finding has important implications for volatility spillovers as discussed below.

*5.2 Volatility spillovers*

We turn now to results from our asymmetric BEKK model. Table 3 provides tests and medians of squared parameter estimates for individual coefficients. At the top of the panel, like Table 2, we provide the proportion of rejections associated with the null that a given parameter is equal to 0. For example, for the matrix A, "CNY → CNY" reports the proportion of rejections of the null that the row-1, column-1 element of A is equal to 0.

The evidence in Table 3 highlights the importance of asymmetry.[14] In particular, for all elements of the matrix *D*, the highest proportion of statistically significant coefficients can generally be found in the final two subsamples. Additionally, the squared median parameter estimates associated with *D* are substantially larger in the final subsample, especially compared to the period prior to the 8-11 reform. Results are especially strong for the elements of *D* associated with CNH-rates. For example, the coefficient restriction connected to offshore markets is rejected 69.02% of the time when analyzing cross-equation impacts during the final subsample, where the same hypothesis was only rejected 14.92% of the time for our samples prior to the 8-11 reform. The results in Table 3 provide preliminary evidence suggesting that asymmetry is an increasingly important feature of RMB-based volatility dynamics.

[14] In a GARCH-in-mean context, Smallwood (2022) shows that the consequences of ignoring existing asymmetry in BEKK models can be quite severe, while modelling non-existent asymmetry is generally less problematic.

## Table 3

Variance Equation Results

| Variance equation: $H_t = CC' + A\epsilon_{t-1}\epsilon'_{t-1}A' + BH_{t-1}B' + D\Xi_{t-1}\Xi'_{t-1}D'$ | | | | | |
|---|---|---|---|---|---|
| Proportion of significant coefficients for identified policy periods | | | | | |
| Coefficient Vector/Matrix | | Pre-811 Period | Transition Period | Two-Pillar Period | Post-COVID |
| **Variance Equation: Shock Impacts** | | | | | |
| $A$ | CNY → CNY | 0.5813 | 0.5744 | 0.3558 | 0.0236 |
| | CNH → CNY | 0.1533 | 0.4073 | 0.2439 | 0.2357 |
| | CNY → CNH | 0.4475 | 0.5561 | 0.3280 | 0.1515 |
| | CNH → CNH | 0.4794 | 0.5011 | 0.3297 | 0.1886 |
| **Variance Equation: Volatility Impacts** | | | | | |
| B | CNY → CNY | 0.9270 | 0.5904 | 0.5484 | 0.9630 |
| | CNH → CNY | 0.1080 | 0.3822 | 0.1775 | 0.2795 |
| | CNY → CNH | 0.1770 | 0.4851 | 0.2237 | 0.2896 |
| | CNH → CNH | 0.9434 | 0.9336 | 0.6888 | 0.9764 |
| **Variance Equation: Asymmetric Shock Impacts** | | | | | |
| D | CNY → CNY | 0.2325 | 0.1167 | 0.2944 | 0.3973 |
| | CNH → CNY | 0.1492 | 0.0801 | 0.3574 | 0.6902 |
| | CNY → CNH | 0.0566 | 0.2380 | 0.2372 | 0.4848 |
| | CNH → CNH | 0.2088 | 0.2471 | 0.2590 | 0.7340 |
| Median Parameter Estimates | | | | | |
| | | Pre-811 Period | Transition Period | Two-Pillar Period | Post-COVID |
| A ($a_{i,j}^2$) | **ARCH** | | | | |
| | CNY → CNY | 0.1682 | 0.3640 | 0.1487 | 0.0574 |
| | CNH → CNY | 0.0106 | 0.0570 | 0.0621 | 0.0505 |
| | CNY → CNH | 0.1236 | 1.1246 | 0.2041 | 0.1612 |
| | CNH → CNH | 0.0662 | 0.3178 | 0.1560 | 0.1064 |
| B ($b_{i,j}^2$) | **GARCH** | | | | |
| | CNY → CNY | 0.5919 | 0.4424 | 0.5741 | 0.6081 |
| | CNH → CNY | 0.0100 | 0.0160 | 0.0643 | 0.0130 |
| | CNY → CNH | 0.0265 | 0.7129 | 0.1525 | 0.0556 |
| | CNH → CNH | 0.6603 | 0.8090 | 0.8058 | 0.9810 |
| D ($d_{i,j}^2$) | **ASYMMETRIC COEFFICIENTS** | | | | |
| | CNY → CNY | 0.0921 | 0.2073 | 0.2662 | 0.3424 |
| | CNH → CNY | 0.0098 | 0.0385 | 0.2938 | 0.6103 |
| | CNY → CNH | 0.0837 | 0.4650 | 0.2149 | 0.5626 |
| | CNH → CNH | 0.0728 | 0.3543 | 0.2743 | 0.9723 |

*Notes*: In the bottom panel of the table, we report the median of the squared values of the parameters given the quadratic nature of the model. See Table 2 for additional details about the interpretation of test statistics and the time periods used for splitting various subsamples.

To fully understand volatility transmission, we must conduct tests of joint hypotheses connected to the elements of *A*, *B*, and *D*. Accordingly, Table 4 provides summary evidence for various hypotheses across each of our four identified policy periods. Specific details regarding various restrictions can be found in the table. In Figure 2, we provide a plot of the Wald test statistics for all time periods associated with two null hypotheses. The test associated with potential spillovers from the offshore to the onshore market is associated with the null that $a_{1,2}=b_{1,2}=d_{1,2}=0$. The corresponding test for spillovers from the onshore market is connected to the hypothesis $a_{2,1}=b_{2,1}=d_{2,1}=0$. With three restrictions, the critical value as depicted in the figure is 7.815.

# Table 4

Joint Parameter Hypotheses

| Variance Equation: $H_t = CC' + A\epsilon_{t-1}\epsilon_{t-1}'A' + BH_{t-1}B' + D\Xi_{t-1}\Xi_{t-1}'D'$ | | | | | |
|---|---|---|---|---|---|
| Restriction | | Pre-811 Period | Transition Period | Two-Pillar Period | Post COVID |
| | **VARIANCE EQUATION: NO SHOCK SPILLOVER** | | | | |
| $a_{1,2} = d_{1,2} = 0$ | CNH → CNY | 0.2850 | 0.3799 | 0.5257 | 0.8418 |
| $a_{2,1} = d_{2,1} = 0$ | CNY → CNH | 0.4444 | 0.5812 | 0.4886 | 0.4579 |
| | **VARIANCE EQUATION: NO SHOCK OR VOL. SPILLOVER** | | | | |
| $a_{1,2}=b_{1,2}=d_{1,2}=0$ | CNH → CNY | 0.3457 | 0.6407 | 0.5559 | 0.8889 |
| $a_{2,1}=b_{2,1}=d_{2,1}=0$ | CNY → CNH | 0.4784 | 0.6751 | 0.5299 | 0.5320 |
| $a_{i,j}=b_{i,j}=d_{i,j}=0$ all $i \neq j$ | NO SPILLOVER | 0.5309 | 0.8307 | 0.7637 | 0.8889 |
| **VARIANCE EQUATION: NO ASYMMETRY** | | | | | |
| $D$=0 | No asymmetry | 0.5525 | 0.5309 | 0.6972 | 0.9798 |

*Notes*: For every 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. A lack of shock spillovers is tested via hypotheses related to off-diagonal elements in *A* and *D*, while restrictions on *A*, *B*, and *D* can be used to test a null of no shock or volatility spillovers. In the last panel, symmetry in $H_t$ is tested using a Wald test associated with the 4 restrictions that all elements in *D* are jointly zero. Please see Tables 2 and 3 for more detail on the relevant subsamples.

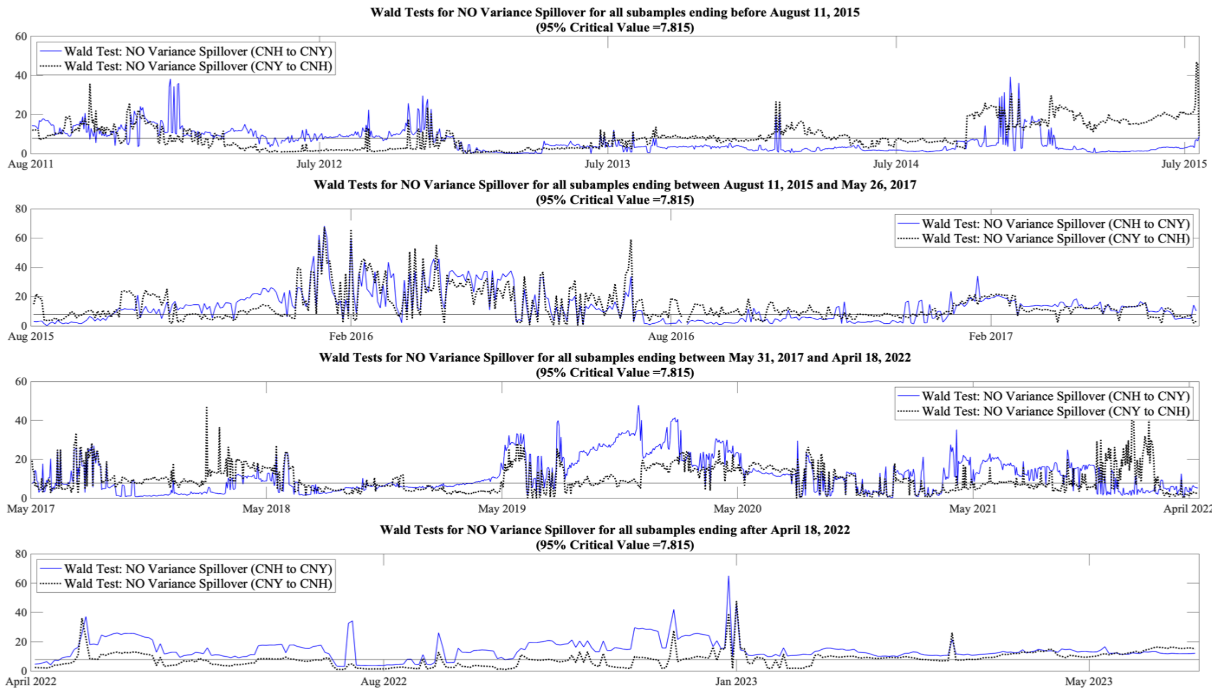


Figure 2: Wald Test Statistics for Hypothesis $a_{i,j} = b_{i,j} = d_{i,j} = 0, i \neq j$

The evidence demonstrates that spillovers from one market to the other appear to be highly time varying, with evidence that CNY volatilities most strongly impacted offshore markets in the earlier subsamples. In Table 4, for example, we see that during the transition period, spillovers are detected 67.51% of the time. Referring to the second panel in Figure 2, we observe that evidence of spillovers was especially strong in the immediate aftermath of the 8-11 reform. For remaining subsamples, the proportion of rejections hovers around 50%. At the same time, evidence of spillovers from the offshore market has clearly been strengthening, with rejection rates that increased from 34.57% for the first subsample to 88.89% during the most recent periods. The dominance of the offshore market is reinforced in Figure 2, where one observes a larger test statistic for CNH-based spillovers relative to CNY-based counterparts for nearly every subsample during the final period.

The surprising rise in the importance of the offshore market is accompanied by a stark increase in the relative importance of asymmetry, as seen by an overwhelming rejection of the null of symmetry in the conditional variance matrix for our final sample. From Table 4, the null that all elements of *D* are 0 is rejected 97.98% of the time. As discussed above, the negative skew associated with CNH disturbances after COVID shows that unexpected weakness in the offshore market was rampant. As a by-product, given the elevated role of asymmetry in the final sample, we find that CNH markets were largely responsible for recent elevated onshore volatility. As shown below, this hypothesis is also strongly supported by our impulse response analysis.

Our findings related to volatility spillovers deviate from prior studies that take a static approach and employ standard inference, such as Hu et al. (2023), who provide slightly stronger evidence the onshore markets dominate volatility spillovers. Our results are also different from Zhao et al. (2021) who use Granger causality tests and fail to find evidence of spillovers in either direction, although their directional statistics do indicate a modestly stronger impact of CNH rates.[15] These weaker findings of offshore spillovers are likely partially attributable to assumptions of symmetric volatility spillovers under normality. It should be noted that our findings in this section would be similar to existing research if we employed more restrictive assumptions. Specifically, in results that are available on request, we also estimated a symmetric BEKK model under Gaussian disturbances. Using the Bollerslev-Wooldridge based information matrix for the final sample, we only find significant evidence of volatility spillovers from the offshore market 71% of the time versus 52% for CNY based spillovers. This implies that with the use of more traditional tools, the perceived impact of the offshore market would be

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[15] In a static model using interest rate adjusted NDF contracts and spot rates with dummy variables, Wan et al. (2020) provide evidence that volatility spillovers increase during periods when onshore rates are more flexible.

dramatically reduced. The ability to fully understand the consequences of ignoring asymmetry can best be accomplished through impulse response analysis, which is considered in the next section.

# 6. VIRF analysis and factors driving spillovers

The results in the previous section demonstrate the importance of asymmetric volatility spillovers, which appear to be especially important in understanding the dynamics of the offshore market. A natural question that arises is how does the existence of asymmetry impact the relative dominance of CNY and CNH rates in spillovers? Additionally, what factors drive the relative strength of each market, particularly when the RMB depreciates unexpectedly? In Section 6.1, we employ extensive simulations based on volatility impulse response functions (VIRFs). The VIRFs are used to derive directional statistics and net spillover indices, which are subsequently modelled as a function of policy variables and economic fundamentals in Section 6.2.

*6.1 Impulse response analysis*

Hafner and Herwartz (2006) and Shields et al. (2005) provide methods to measure the VIRF based on the generalized impulse response function originally proposed by Koop et al. (1996). The VIRF ultimately measures the difference between two conditional *n*-step ahead forecasts for the conditional variance matrix given an initial history. Our methods for calculating the VIRF closely follows Shields et al. (2005) and Green et al. (2018), with full details and definitions available in the Appendix.

To obtain summary statistics that provide information related to the feedback between CNY and CNH volatilities, we use total and directional spillovers as studied by Diebold and Yilmaz (2012). For the VIRF, for a given history $\omega_{t-1}$, $\lambda_{ij,\omega_{t-1}}(h)$ is the relevant statistic that measures the contribution of a shock to the *j*-th variable on the conditional variance of the *i*-th residual, relative to shocks to both variables (see, Lanne and Nyberg, 2016). For a horizon *n,* let $VIRF(n, \delta_{jt}, \omega_{t-1})_i$ denote the VIRF for the *i*-th conditional variance given a shock of size $\delta_{jt}$ to the *j*-th variable. Then, $\lambda_{ij,\omega_{t-1}}(h)$ is,

$$\lambda_{ij,\omega_{t-1}}(h) = \frac{\sum_{n=1}^{h} VIRF\left(n, \delta_{jt}, \omega_{t-1}\right)_i^2}{\sum_{j=1}^{2}\sum_{n=1}^{h} VIRF\left(n, \delta_{jt}, \omega_{t-1}\right)_i^2} \; i, j = 1,2. \qquad (7)$$

Suppressing notation for the history and horizon, $\lambda_{12}$ measures the contribution of shocks to CNH returns on the CNY-based conditional variance relative to the aggregate impact of all shocks on the CNY-based conditional variance. The reverse is captured by $\lambda_{21}$. 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 spillovers, we analyze the statistic $NET_k$=0.5($\lambda_{12}^{(k)} - \lambda_{21}^{(k)}$). If $NET_k$>0, this implies off-shore markets have a relatively large spillover impact, whereas negative values imply the relative dominance of CNY-based shocks and volatilities. The directional statistics complement the VIRFs found in Figure 3 and can be found in Table 5 below.

Turning to Figure 3, we report the median values of the VIRFs across each of our four identified policy periods. In the panels on the left side, 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 $\hat{\sigma}_{z_{CNY}}$ denoting the standard deviation of the independent innovations for CNY returns, $\delta_{CNY+} = 2\hat{\sigma}_{z_{CNY}}$, and $\delta_{CNY-} = -\delta_{CNY+}$. Analogous meaning is ascribed to $\delta_{CNH+}$ and $\delta_{CNH-}$.

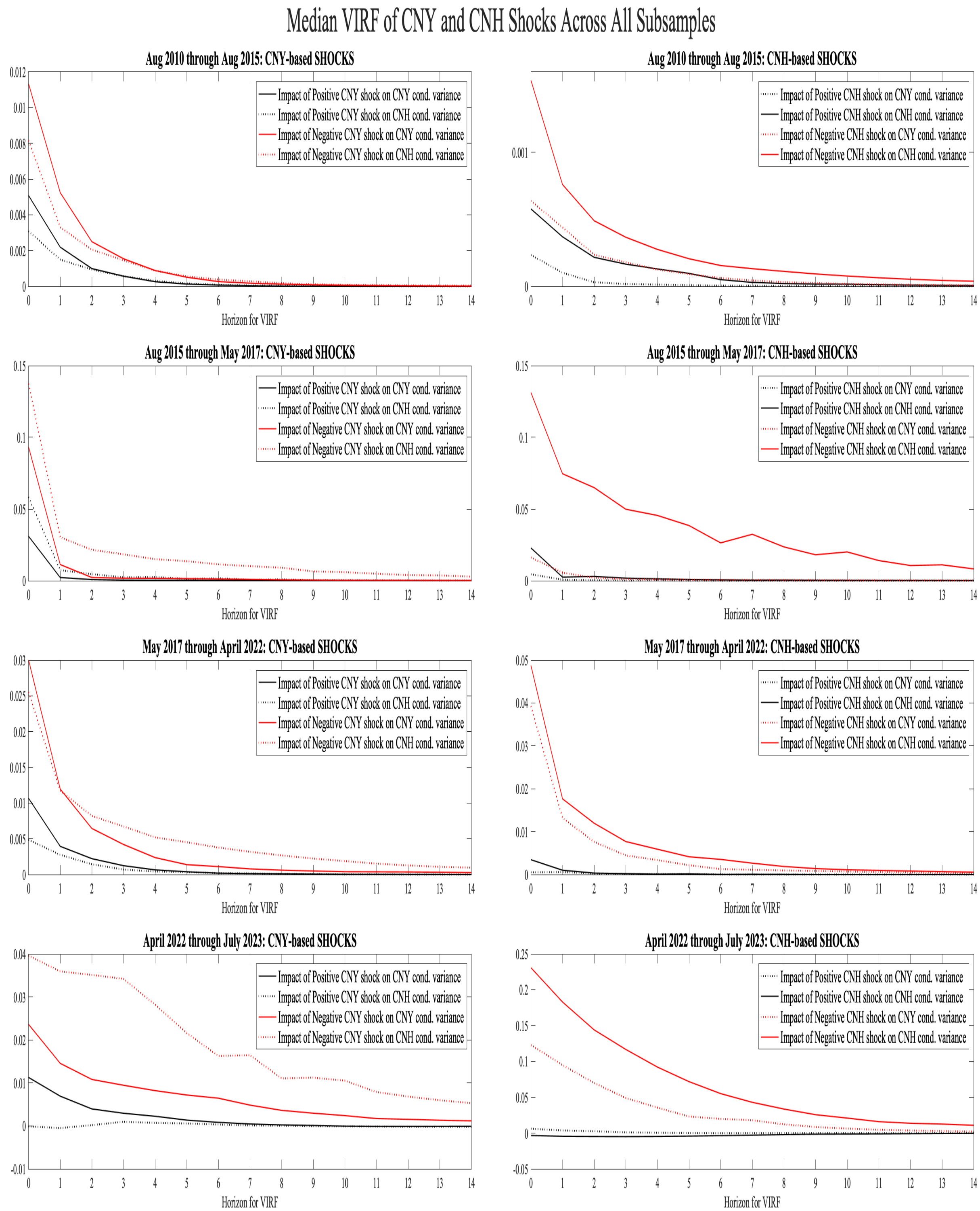


Figure 3: Median VIRF (Dotted lines represent cross-equation impacts)

# Table 5

VIRF Analyses

| Subsample | | | | |
|---|---|---|---|---|
| Statistic | Pre-811 Period | Transition Period | Two-Pillar | Post COVID |
| Variance Equation Effects: ***Positive*** 2-std deviation shock | | | | |
| Statistic | | | | |
| Prop. of $NET_k$>0 | 0.4640 | 0.3295 | 0.4172 | 0.7778 |
| Median $NET_k$ | -0.1616 | -0.3031 | -0.1055 | 0.1942 |
| Median $TOTAL_k$ | 0.4275 | 0.4821 | 0.4774 | 0.4756 |
| Variance Equation Effects: ***Negative*** 2-std deviation shock | | | | |
| Prop. of $NET_k$>0 | 0.4897 | 0.3776 | 0.6098 | 0.9899 |
| Median $NET_k$ | -0.0047 | -0.0962 | 0.0966 | 0.4139 |
| Median $TOTAL_k$ | 0.3828 | 0.4556 | 0.4825 | 0.4972 |
| | Pre-811 Period | Tran. Period | Two-Pillar | Post-COVID |
| Variance Equation Effects: Extreme ***positive*** shock (99% from empirical distribution of $z_t$) | | | | |
| Statistic | | | | |
| Prop. of $NET_k$>0 | 0.4156 | 0.2243 | 0.4760 | 0.5185 |
| Median $NET_k$ | -0.3688 | -0.3521 | -0.0431 | 0.0319 |
| Median $TOTAL_k$ | 0.4819 | 0.4770 | 0.4854 | 0.4741 |
| Variance Equation Effects: Extreme ***negative*** shock (1% from empirical distribution of $z_t$) | | | | |
| Prop. of $NET_k$>0 | 0.6121 | 0.3501 | 0.6156 | 0.9899 |
| Median $NET_k$ | 0.1158 | -0.1004 | 0.2188 | 0.4778 |
| Median $TOTAL_k$ | 0.3734 | 0.3986 | 0.4858 | 0.4987 |

*Notes*: The Table summarizes statistics related to the VIRFs. If *NET*>0, 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 impact of a CNY-shock on the CNH variable. *TOTAL* measures the impact of spillover shocks relative to all shocks. For each subsample, we provide the proportion of cases where *NET>0*, along with median values for *NET* and *TOTAL* for different shocks. Positive/negative "2-std deviation shocks" use twice the standard deviation of $z_t$ (the "baseline case"). Shocks are otherwise drawn from the empirical distribution of $z_t$.

The results yield crucial information about the dynamics of the two RMB markets. First, from a historical perspective, onshore shocks dominate during our transition period. Clearly, as policy makers alter the mechanism for setting the daily parity rate, markets begin to react. This is evidenced in Table 5, where the proportion of positive *NET* statistics is substantially less than 50%, regardless of how shocks are drawn. Under extreme appreciations, perhaps due to interventions aimed at stemming capital outflow, the value of *NET* was positive in only 22.43% of the relevant samples. The findings during the transition period are reinforced through inspection of Figure 3, where cross-border impacts (given by dashed lines) only materialize when analyzing onshore spillovers to the offshore market. For all sub-sample splits, except for the Pre-811 Period, we observe that onshore shocks tend to impact the offshore market even more than domestic volatilities. This suggests that traders on the mainland may have been more aware of potential policy changes.

From Table 5, the growing importance of the offshore market is seen during our last subsample, where the *NET* statistic is greater than 50% no matter how shocks are drawn. Except for the transition period, as noted above, we see that under unexpected depreciations of the RMB, CNH-based shocks have a larger relative impact in nearly every sample, including the Two-Pillar period. Not surprisingly, in results that are available on request, we find that the *NET* statistic under RMB weakness briefly turned negative at the onset of COVID. Even still, under unexpected RMB weakness, our *NET* statistic exceeds zero more than 60% of the time for all subsamples from 2017-2022. More generally, the offshore market appears clearly more important when shocks are negative, as the *NET* statistic is always larger under negative shocks relative to positive shocks. This finding is highlighted in the final two panels on the right-hand side of Figure 3, where positive shocks have a very modest cross-border impact, with huge effects when the RMB depreciates unexpectedly. The differences can be even more substantial when shocks are drawn from the tails of the empirical distributions of residuals from our estimated model. For example, from Table 5, offshore markets dominate 51.85% of the time when the RMB unexpectedly appreciates. In contrast, the offshore market dominates with near unanimity for extreme unexpected depreciations.[16]

[16] In addition to the more granular results here, we also obtained estimation findings using all observations within a given subsample instead of using rolling subsamples. The results are available on request and show that for both types of shocks, the value of *NET* is larger under RMB weakness relative to strength for all subsamples except the transition period. We are grateful to an anonymous reviewer for suggesting these findings, which support our conclusion that the offshore market is more likely to dominate spillovers in late samples under RMB weakness.

Overall, these results show that the offshore market is growing in importance, particularly under unexpected depreciations of the RMB. Additionally, the distribution can matter, since the relative differences in impacts can be especially acute when news emanates from the tails of the empirical densities. For example, as discussed above, we estimated symmetric BEKK models estimated under a Gaussian assumption. The results, available upon request, show that the *NET* statistic is equal to 0.60 under both positive and negative two-standard deviation shocks for the last subsample. Not surprisingly, the results are virtually identical if we use shocks drawn from the tails of the distribution, since a Gaussian assumption imposes symmetry.

*6.2 Factors driving spillover dominance*

Our findings provide additional context for research on volatility spillovers that has concluded offshore markets exert a growing influence on the RMB market (see, for example, Wan et al. 2020 and Funke et al., 2022). In contrast to existing literature, we can characterize the strength of the volatility relationships under both RMB strength and weakness. It would be of additional interest to investigate the factors that influence the strength of volatility spillovers between the onshore and offshore markets. Although several papers have explored factors influencing the conditional variance of RMB exchange rate returns and their differentials, to our knowledge, no study has attempted to determine what drives the relative importance of each market in volatility spillovers.[17] To address the void within existing research, we consider regression analysis using our *NET* variables, following a large literature that studies factors driving connectedness among asset classes and across financial markets using dependent

[17] Funke et al. (2015) and Liang et al. (2019) show that various exchange rate policy changes impact the conditional variance of exchange rate differentials. Liang et al. (2019) also consider additional controls such as the bid-ask spread in the offshore market. Ho, Shi, and Zhang (2018) and Liang et al. (2019) use multivariate GARCH methods to analyze the conditional correlation between exchange rates in the onshore and offshore market. Liang et al. (2019), for example, use the dynamic conditional correlation model and demonstrate a stronger connection between the markets after the 8-11 reform. None of these studies attempt to determine what factors drive the relative importance of each market in volatility spillovers.

variables derived from spillover statistics.[18] To more naturally interpret our *NET* statistics, they are adjusted to take on values between 0 and 1, where values near 0 imply that the onshore market is solely responsible for spillovers. Values near 1 are associated with complete dominance of the offshore market.

From our discussion above, we assert that the offshore market is most likely to dominate spillovers in recent samples as the PBoC withdraws currency support. Further, when the RMB weakens unexpectedly, we contend that information flows are more likely to spillover from CNH to CNY rates under more open capital markets and a more flexible currency. Above, we provide incomplete evidence supporting these hypotheses, given the finding of an increasing proportion of positive *NET* statistics under negative shocks. Therefore, the most critical variables related to our analysis include a measure of official intervention (*RES*) and capital flows (*FLOW*). For additional controls, we considered numerous variables following the existing literature that provides some guidance, albeit not directly related to RMB volatility spillovers. Specifically, we added the ratio of the difference between the daily ask and bid rates for the CNH market relative to the onshore market (*RATIO*), along with the difference between onshore and offshore equity returns (*STOCK*). Funke et al. (2015), Liang et al. (2019), and Sun et al. (2020) found similar variables to be relevant in their analyses related to RMB differentials and associated conditional volatilities. Following Sun et al. (2020), we also include the difference between the offshore HIBOR and the onshore SHIBOR rates (*SPREAD*). Finally, to control for sentiment in the global economy, we included the measure of consumer confidence as reported by the University of Michigan (*CC*). Complete variable definitions can be found in Table A.4 in the Appendix.

[18] Examples include Tsai (2014), Fernandez-Rodriguez et al. (2016), Yang and Zhou (2017), Rohit and Dash (2019), Wang et al. (2023), and Feng et al. (2023). Feng et al. (2023), for example, conclude that cross-border exchange rate spillovers are driven primarily by economic fundamentals and monetary policy using net statistics for 21 countries.

To more formally assess the drivers of volatility spillovers, we consider the following model, where $\eta_t$ denotes a set of residuals,

$$NET_t^i = c + \gamma_1^i RES_t + \gamma_2^i FLOW_t + \gamma_3^i CC_t + \gamma_4^i RATIO_t + \gamma_5^i STOCK_t + \gamma_6^i SPREAD_t + \eta_t. \quad (8)$$

Here, $NET_t^i$ denotes the value of the net-statistic at time-$t$ for shock-type "$i$" .[19] Here, there are four different shocks analyzed. We consider the cases of positive/negative shocks given by +/- twice the standard deviation of $z_t$. We also consider our *NET* statistics based on shocks drawn from the first and 99th percentile of the empirical distribution of $z_t$.

Our assertion that offshore markets should exhibit an increasing influence under negative shocks as official intervention is withdrawn and capital flows increase is supported if $\gamma_1^i < 0$ and $\gamma_2^i > 0$, when $i$ corresponds to negative shocks. For additional controls, we generally expect $\gamma_3^i$ to be negative. High levels of US-based confidence are likely associated with the perception of a healthy global economy. In this environment, information might be expected to flow from the onshore to offshore market given benign international conditions. In general, the expected signs of other coefficients are somewhat ambiguous. For example, as the gap between the offshore bid and ask spread grow, CNH-based uncertainty might be expected to increase (see, Bollerslev and Melvin, 1994). Particularly under negative shocks, a positive value of $\gamma_4^i$ might be expected as the relative increase in offshore uncertainty is expected to be higher, creating larger spillover effects to the onshore market. The higher costs in the offshore market could also signal a relatively liquid onshore currency, where we might expect information could flow from the

[19] We considered additional controls including the VIX, a policy uncertainty index for China, and the difference between the central parity rate and the previous day's spot CNY closing price. In general, the inclusion of these additional controls resulted in a poorer fit or statistical insignificance. Following Funke et al. (2015), these variables have been excluded from our final model, with results available on request. Our central conclusions related to official intervention and capital flows are robust to the inclusion of these variables. Prior studies have found a limited role for VIX in RMB dynamics (see, for example, Sun et al., 2020), while Funke et al. (2015) reports a limited role for surprise announcements regarding fundamentals.

onshore to offshore trading centers. Prior studies have found that differences in equity-returns and interest rates are relevant for RMB dynamics, although the impact on the relative importance of each currency was found to be time-varying and ambiguous by Sun et al. (2020) in their analysis using interval-based methods. The variable *STOCK* has been found to be an important series capturing both the risk-premium in onshore markets and economic fundamentals. Higher rates of return in the onshore market might be associated with a discount on CNH, elevated risk in the onshore market, or a reflection of a relatively healthy Chinese economy (see Funke et. al., 2015 and Sun et. al, 2020). The impact of shocks on CNY and CNH based volatility might, therefore, be expected to be time varying depending on which factor most dominates the higher onshore share prices. Similarly, a higher spread between HIBOR and SHIBOR could reflect differences in monetary policy, borrowing preferences, or reduced liquidity in the offshore markets. Overall, the expected influence of *STOCK* and *SPREAD* on the strength of volatility spillovers is ambiguous and remains an empirical issue we now explore.

There might be some concern in the current context as values near the boundaries of 0 and 1 are not uncommon. Therefore, in Table 6, we report results using the fractional logit methodology pioneered by Papke and Wooldrige (1996) with robust standard errors. The first set of findings in Tables 6a report results under two-standard deviation shocks, while those in Table 6b yield findings for shocks drawn from the tails of the empirical distributions. For robustness, we also obtained results using least squares estimation with the standard errors of Newey and West (1994). For brevity, these findings are not included here, although they generally support our conclusions reached below. The findings are available on request.

Table 6a
Determinants of NET volatility spillovers
Two-std deviation shocks: Fractional Logit with Robust Standard Errors

| Positive Shocks | | | | | | |
|---|---|---|---|---|---|---|
| | | Full Sample | 2010-2015 | 2015-2017 | 2017-2022 | 2022-Today |
| Variable | | | | | | |
| *RES* | | -0.028*** | -0.048*** | -0.244*** | -0.042* | 0.0514 |
| | | [0.004] | [0.008] | [0.038] | [0.023] | [0.057] |
| *FLOW* | | 0.817*** | -0.092 | 0.290 | -1.279*** | 9.370*** |
| | | [0.062] | [0.157] | [0.776] | [0.186] | [1.132] |
| *CC* | | -0.068*** | -0.388*** | -0.676** | 0.107*** | -0.209** |
| | | [0.005] | [0.027] | [0.270] | [0.021] | [0.090] |
| *RATIO* | | 0.705*** | -0.054 | 1.353*** | 0.477*** | -3.062*** |
| | | [0.026] | [0.068] | [0.229] | [0.114] | [0.611] |
| *STOCK* | | -0.006 | 0.026 | 0.194*** | -0.053** | 1.669*** |
| | | [0.005] | [0.016] | [0.050] | [0.025] | [0.199] |
| *SPREAD* | | 0.074 | 1.030*** | 1.356** | -0.095 | -5.237*** |
| | | [0.049] | [0.110] | [0.614] | [0.217] | [1.730] |

| Negative Shocks | | | | | | |
|---|---|---|---|---|---|---|
| Variable | | | | | | |
| *RES* | | -0.020*** | -0.001 | -0.087** | -0.179*** | -0.233*** |
| | | [0.003] | [0.006] | [0.035] | [0.017] | [0.051] |
| *FLOW* | | 1.143*** | 0.645*** | 3.019*** | 0.485*** | 4.832*** |
| | | [0.048] | [0.127] | [0.641] | [0.139] | [1.167] |
| *CC* | | -0.109*** | -0.301*** | -1.585*** | -0.171*** | -0.362*** |
| | | [0.004] | [0.020] | [0.314] | [0.016] | [0.119] |
| *RATIO* | | 0.492*** | -0.061 | 1.400*** | -0.231*** | -4.947*** |
| | | [0.021] | [0.054] | [0.263] | [0.081] | [0.647] |
| *STOCK* | | 0.000 | 0.044*** | 0.111*** | -0.070*** | 0.435** |
| | | [0.003] | [0.009] | [0.038] | [0.019] | [0.192] |
| *SPREAD* | | 0.069* | 1.063*** | -0.736 | 0.013 | 1.670 |
| | | [0.038] | [0.079] | [0.511] | [0.144] | [1.400] |

*Notes: In brackets, we report robust standard errors, where parameters are estimated using the fractional logit model introduced by Papke and Wooldridge (1996). *, **, *** denote statistical significance based on a 10%, 5%, and 1% test-size respectively. Shocks are given by twice the standard deviation of $z_t$ for each series.*

Table 6b
Determinants of NET volatility spillovers
Extreme shocks: Fractional Logit with Robust Standard Errors

| Positive Shocks | | | | | | |
|---|---|---|---|---|---|---|
| | | Full Sample | 2010-2015 | 2015-2017 | 2017-2022 | 2022-Today |
| Variable | | | | | | |
| *RES* | | -0.051*** | -0.103*** | -0.184*** | -0.018 | -0.320*** |
| | | [0.004] | [0.010] | [0.038] | [0.027] | [0.066] |
| *FLOW* | | 0.683*** | -1.565*** | 3.029*** | -1.656*** | 9.539*** |
| | | [0.070] | [0.206] | [0.667] | [0.219] | [1.585] |
| *CC* | | -0.069*** | -0.476*** | -1.258*** | 0.253*** | -0.359*** |
| | | [0.006] | [0.028] | [0.281] | [0.250] | [0.097] |
| *RATIO* | | 0.656*** | -0.150** | 1.427*** | 0.357*** | -4.433*** |
| | | [0.027] | [0.059] | [0.240] | [0.124] | [0.677] |
| *STOCK* | | -0.036*** | 0.056*** | 0.048 | 0.079*** | 2.406*** |
| | | [0.005] | [0.021] | [0.048] | [0.030] | [0.279] |
| *SPREAD* | | 0.420*** | 1.387*** | -0.412 | 1.409*** | -7.495*** |
| | | [0.057] | [0.122] | [0.546] | [0.252] | [2.396] |
| | | | | | | |
| Negative Shocks | | | | | | |
| Variable | | | | | | |
| *RES* | | -0.037*** | -0.007 | -0.035 | -0.269*** | -0.280*** |
| | | [0.003] | [0.007] | [0.029] | [0.020] | [0.079] |
| *FLOW* | | 0.869*** | 0.553*** | 4.425*** | 0.697*** | 3.996** |
| | | [0.055] | [0.142] | [0.499] | [0.157] | [1.930] |
| *CC* | | -0.092*** | -0.230*** | -2.212*** | -0.267*** | -0.470** |
| | | [0.005] | [0.025] | [0.290] | [0.019] | [0.198] |
| *RATIO* | | 0.516*** | 0.110 | 1.478*** | -0.121 | -4.240*** |
| | | [0.024] | [0.071] | [0.234] | [0.100] | [1.025] |
| *STOCK* | | 0.019*** | 0.024** | 0.134*** | -0.131*** | 0.373 |
| | | [0.004] | [0.011] | [0.032] | [0.022] | [0.300] |
| *SPREAD* | | -0.303*** | 0.874*** | -2.751*** | -1.677*** | 1.015 |
| | | [0.051] | [0.106] | [0.404] | [0.164] | [2.080] |

*Notes: In brackets, we report robust standard errors, where parameters are estimated using the fractional logit model introduced by Papke and Wooldridge (1996). *, **, *** denote statistical significance based on a 10%, 5%, and 1% test-size respectively. Shocks are drawn from the first and 99th percentile for* $z_t$ .

Turning to the results, under RMB weakness, there is strong support for our hypothesis that offshore markets are expected to increasingly dominate information flows in more recent samples when the PBoC is less active. Under both types of negative shocks, the coefficient on our official reserve variable is always negative and is statistically significant for all subsamples after 2017. When official intervention falls, our *NET* statistics tend to rise, suggesting asymmetric herding may occur as traders assimilate information in the offshore market. The same finding is absent when exploring positive shocks. For example, from Table 6a, the coefficient is positive for the last subsample under two-standard deviation shocks, and in Table 6b, it is insignificantly negative for the subsample from 2017-2022 under extreme shocks. Perhaps more importantly, there is resounding support for the assertion that under stronger capital flows, the offshore market is expected to dominate volatility spillovers when the yuan weakens unexpectedly. From Table 6a and 6b, we see that the coefficient on our *FLOW* variable is unambiguously positive and statistically significant for both types of negative shocks and for all subsamples. In contrast, under positive shocks, the findings are more mixed. For example, in both Table 6a and Table 6b, we see that the coefficient on *FLOW* is significantly negative when the RMB appreciates in value for the sample running from 2017-2022. It seems reasonable to conclude that during this time, as capital flows intensified, the PBoC implemented supportive policies related to RMB strength causing spillovers from the mainland to offshore centers.

The results show that changes in official reserves and stronger capital flows are responsible for the strong volatility spillovers from offshore markets under unexpected RMB weakness. Additionally, there is strong support for the assertion that US economic instability, as measured through US-based consumer confidence, is associated with stronger spillovers from the offshore market. As we see, particularly under negative shocks, the coefficient on our CC variable is nearly always statistically significant and negative. The implications are that as economic instability increases, consumer confidence declines. The information is subsequently transmitted from the offshore to the onshore. As expected, the effects of our remaining control variables are somewhat ambiguous and time varying. For the full sample, under all types of shocks and estimation methods, the coefficients on our *RATIO* variable are positive and statistically significant. This supports the view that a higher offshore bid-ask spread is associated with more offshore uncertainty. The evidence for our subsamples is more mixed. For the *STOCK* variable, there is slightly more evidence across our four subsamples that a higher premium in Shanghai is associated with stronger spillovers from the offshore market.

Curiously, we see that there appear to be differences in terms of how interest rate differentials affect the strength of spillovers for the specification where shocks are drawn from the tails of our empirical distributions. In particular, from Table 6b under negative shocks, an increase in interest rate differentials is more generally associated with stronger spillovers from CNY to CNH volatilities, while the reverse holds under positive shocks. One possibility could be that when a very weak CNY rate is coupled with a relatively low SHIBOR rate, it reflects an official desire to stimulate the economy through currency depreciation and lax monetary policy. In these cases, onshore shocks are expected to generate a larger impact on CNH-based volatilities. Overall, the findings on our additional controls are not as strong as the results for changes in reserves, capital flows, and US-based consumer confidence, suggesting these three variables are likely the most important in explaining the strength of spillovers between the two renminbi markets.

# 7. Conclusion

The manuscript adds new insight into the relationship between the onshore and offshore RMB markets by focusing on the evolutionary features of the relative strength of each market. Our analysis shows that as RMB exchange rate management has evolved, so too has the relationship between CNH and CNY exchange rates. While evidence shows that both CNH and CNY rates contributed to return spillovers prior to the 8-11 reform, feedback is now much more likely to run from the offshore to onshore market. Additionally, the relationship between onshore and offshore volatilities has changed, where asymmetry has emerged as a crucial feature of the dynamics between the two markets. Most notably, the results reveal that under RMB weakness, the offshore market is more likely to dominate information flows in our most recent samples. Finally, regression results demonstrate that increased capital flows and a decline in official intervention are important factors driving the strength of volatility spillovers, particularly under unexpected RMB weakness.

Our empirical findings have important implications for policy makers in China, who have attempted to simultaneously internationalize the RMB and maintain exchange rate stability. On one hand, spillovers can be used by policy makers to obtain information regarding the assessment of the market to internal and external changes. The existence of spillovers under RMB weakness, in particular, can be used to gauge the potential for enhanced speculation and possible crises. If a need arises to blunt CNH weakness, direct intervention in the offshore market might not be recommended as it is both costly and undermines the role of the offshore trading center as a free market. In rare instances, China could explore the use of macroprudential policies, including changes to the flexible reserve ratio for offshore banks maintaining deposits in mainland banks. More importantly, it is suggested that China continue to provide transparent information related to changes to exchange rate policy, particularly when those changes could be interpreted as suggesting a preference for a weaker yuan. Effective communication could be used to avoid asymmetric herding under heterogenous information that could create a negative feedback loop where misinterpreted signals lead to heightened offshore volatility that spills over and impacts China.

Once the capital account in China is fully open and the onshore currency is traded without restrictions, RMB segmentation will give way to a unified market-oriented Chinese exchange rate. Our finding that the offshore rate has started to take on a more dominant role in spillovers indicates that the pace of marketization is increasing. The transition can be aided by the removal of remaining regulations, such as those that restrict onshore trading that is perceived as lacking a transaction-backed principle in the retail market. Once the onshore market has fully matured, possessing depth and information efficiency, it seems likely that the capital account can fully open, ushering in the existence of a single, unified market for the Chinese currency.

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# A. Appendix

*A.1 Testing for structural breaks in the unconditional variance of returns.*

We describe here the methodology of Sansó et al. (2004), which was used to calculate the modified iterative constrained sum of squared (ICSS) test statistics for breaks in the unconditional variances of exchange rate returns. Importantly, the modified ICSS method can be applied to test for multiple breaks for a wide variety of dependent processes.

Let $\tilde{r}_t^2$ denote the square of either the original return series or an associated set of residuals, and let $c_k = \sum_{t=1}^{k} \tilde{r}_t^2$. For a sample of size *T*, the test statistic, denoted *MIT,* is given by

$$MIT = \sup_k \left| \frac{c_k - k/T c_T}{T^{1/2} \hat{\lambda}^{1/2}} \right|, \qquad \text{(a1)}$$

where $\hat{\lambda}$ is estimated using a Bartlett kernel based on the lag truncation parameter, *m*, that is selected via the automated Newey-West (1994) procedure. In particular,

$$\hat{\lambda} = \hat{\gamma}_0 + 2 \sum_{j=1}^{m} \left[ 1 - \frac{j}{m+1} \right] \hat{\gamma}_j \, , \hat{\gamma}_j = \frac{1}{T} \sum_{t=j+1}^{T} \left( \tilde{r}_t^2 - \frac{c_T}{T} \right) \left( \tilde{r}_{t-j}^2 - \frac{c_T}{T} \right), \qquad \text{(a2)}$$

The simulations and response surfaces in Sansó et al. (2004) yield finite sample critical values.[20]

*A.2 Distributional parameters*

We present here the distributional parameters of the models estimated using the multivariate skew Student density function applied to CNY and CNH returns in Section 5 of the manuscript. Figures A1 and A2 provide plots of $1/\hat{\nu}_i$ and $\hat{\xi}_i$, highlighting seemingly obvious departures from normality and evidence of parameter instability. It is important to note that these parameter values are explicitly connected to the multivariate skew-Student density 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.

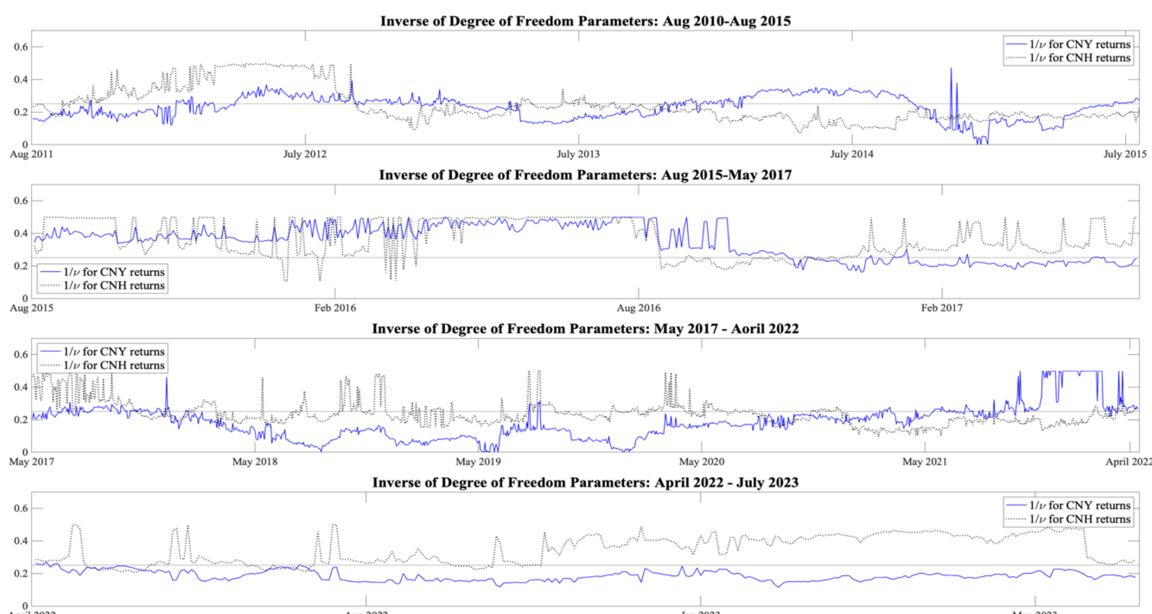


Figure A1: Estimates of $1/\nu_i$ for CNY and CNH Returns

[20] The iterative procedure to obtain multiple breaks is described in Inclan and Tiao (1994), with additional details provided by Rapach and Strauss (2008). Results were obtained using MATLAB code written by the authors that is available on request.

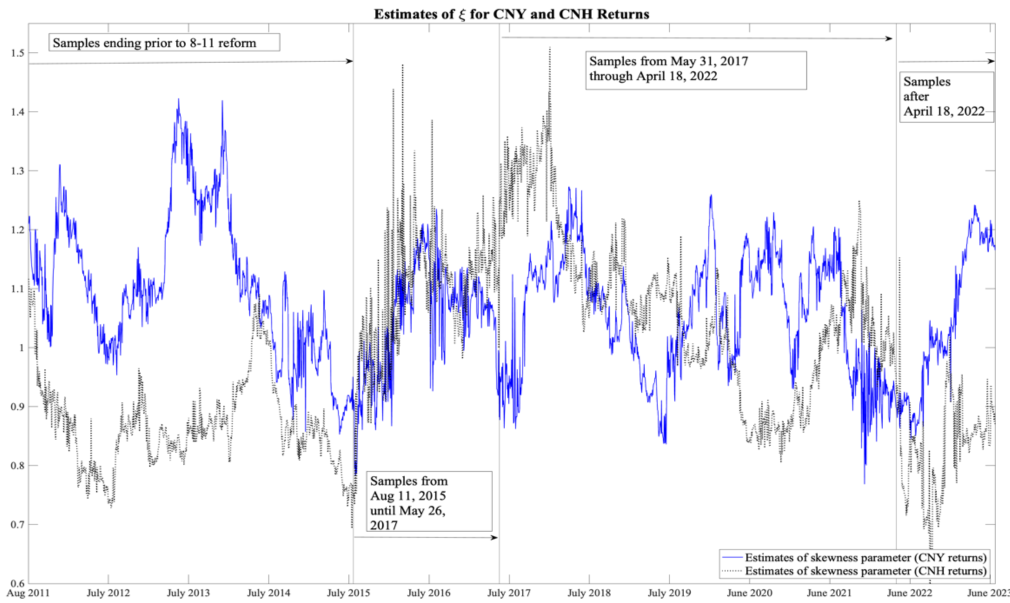


Figure A2: Estimates of $\xi_i$ for CNY and CNH Returns

In Figure A1, statistics exceeding 0.25 represent a degree of freedom parameter less than 4, while values of $\hat{\xi}_i$ in Figure A2 less than (greater than) 1 imply negative (positive) skew. Viewing both figures together, there are several 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 8-11 reform, there appears to be substantial convergence in higher order moments. This is evident from the skewness parameters in Figure A2, where there is little discernible difference between $\hat{\xi}_1$ and $\hat{\xi}_2$. Both sets of innovations also tend to have markedly similar implied kurtoses that are quite large, and potentially infinite, during the transition period. In stark contrast, across remaining samples, there is clear variation between the higher order moments. In fact, as seen in Figure A2, $\hat{\xi}_1$ and $\hat{\xi}_2$ frequently move in opposite directions during our last subsample. It is very relevant to note that only during crisis episodes do we observe an elevated implied kurtosis for CNY rates. For example, at the start of 2020, $\hat{\nu}_1^{-1}$ steadily begins to rise, implying a sharp rise in the kurtosis of unexplained movements in CNY returns at the start of the pandemic. More generally, $\frac{1}{\hat{v}_2} > \frac{1}{\hat{v}_1}$, implying Chinese policy makers have been successful in avoiding unpredictable, extreme changes in the daily onshore spot rates that are more common in the offshore market.

*A.3 Impulse Response Functions*

For the VIRF, let $Q_t = vech(H_t)$, where *vech* is the half vectorization operator that stacks the lower triangular elements of $H_t$. Hafner and Herwartz (2006) define the VIRF at horizon $n$ as,

$$VIRF(n, Z_t, \Omega_{t-1}) = E[Q_{t+n}|Z_t, \Omega_{t-1}] - E[Q_{t+n}|\Omega_{t-1}], \qquad \text{(a3)}$$

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 impulse response functions can condition on a particular shock vector, $z_t = \delta$, and history, $\omega_{t-1}$, yielding the VIRF defined as,

$$VIRF(n, z_t, \omega_{t-1}) = E[Q_{t+n}|z_t = \delta, \omega_{t-1}] - E[Q_{t+n}|\omega_{t-1}]. \qquad \text{(a4)}$$

The associated measure in (a3) can be interpreted as a realization of the random variable in (a4). In the manuscript, we are specifically interested in extreme shocks to news, associated with the tail behavior of the independent innovation, $z_t$, referenced in equation (a4). The empirical distribution is used to draw these shocks, and we also considered a baseline case where shocks are given by twice the standard deviation of the relevant element of $z_t$. We calculate a sequence of VIRFs for each of the 2895 subsamples that each consist of 249 observations, given $P$=1. Figure 3 in the main text of the paper provides the median VIRF across each of our four identified policy-based subsamples.

Below, we provide the steps used in the calculation of the volatility impulse response functions for each of our 2895 subsamples.

i. For each subsample, from the estimated conditional variance matrices ($\widehat{H}_t$) and associated residuals ($\hat{\epsilon}_t$), retrieve the news vector for each time-period in the sample as $\hat{z}_t = \hat{\epsilon}_t \widehat{H}_t^{-1/2}$.

ii. For CNY-based returns, extreme negative ($\delta_{CNY-}$) and positive shocks ($\delta_{CNY+}$) are obtained from the 1st and 99th percentiles of $\hat{z}_t$. 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 the news variables in (i) to obtain *h* bootstrapped innovations, $\{z_{t+n}^*\}$, *n*=0,..,*h*-1. A second set of innovations is obtained that is identical to these, except that the desired element of $z_t^*$ is replaced with the shock from step (ii). Denote these innovations as $\{z_{t+n}^{*\delta}\}$.

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).[21] We have, $\epsilon_{t+n}^* = z_{t+n}^* \widehat{H}_{t+n}^{1/2}$, with analogous meaning for $\epsilon_{t+n}^{*\delta}$.

v. The bootstrapped errors in step (iv) are used to generate two forecasts for the conditional variance matrices using estimated parameters from the asymmetric BEKK model in equation (4) in the main body of the paper. The difference between these two-forecasted values yields the *h* values of the VIRF in equation (a4) above.

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

[21] Following Green et al. (2018), we use the actual estimated conditional variance matrices for each forecasted time period. Coupled with the effect of lagging and differencing, 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.

The procedures in steps (iii)-(vii) are 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.

### *A.4 Variable Definitions for Supplemental Regressions in Section 6*

Table A.1

| Variable and what it proxies | Variable | Definition | Sourse |
|---|---|---|---|
| Official intervention index: Changes in official reserve | RES | 100 multiplied by the ratio of the absolute value of the monthly change in official reserves divided by the absolute value of the maximum monthly change over the course of the sample | Wind |
| Financial openness Capital Flows | FLOW | 100 multiplied by the ratio of financial account assets plus liabilities relative to GDP | Wind |
| Consumer Confidence Index Global Economic Confidence | CC | The Michigan Consumer Confidence Index (MCCI) at the University of Michigan in the United States. | Wind |
| Transactions costs Liquidity | RATIO | (CNH Ask – CNH Bid)/ (CNY Ask – CNY Bid) | Bloomberg |
| Stock market premium: Premium in Shanghai Captures Fundamentals | STOCK | The price difference between A and H shares listed in Shanghai and the and Hang Seng Index in Hong Kong | Wind |
| Interest rate difference Liquidity Monetary policy Borrowing | SPREAD | 1-month HIBOR rate minus 1-month SHIBOR rate | Wind |

Throughout, to obtain a statistic matching our *NET* variable, we average the value of these variables over the relevant time-period for each subsample.