Off-Shore Fears and On-Shore Risk:
Exchange-Rate Pressures and Bank Volatility in China

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Abstract

This research project assesses the effects of news and signals in the off-shore CNH spot market for Chinese currency on the volatility of share prices of Chinese banks and the overall risks of Chinese banking stability. We make use of variance decomposition methods and financial connectedness measures from Vector Autoregressive (VAR) model estimation with machine-learning methods based on LASSO estimation.

Our results show that volatility measures of the offshore CNH market account for over fifty-percent of the share-price volatility forecast-errors of sixteen major banks, during times of off-shore fears, specifically at the time of the downgrading of the US debt, and later, in the period of the Brexit process and the start of US-China trade frictions. The CNH market volatility has practically identical contagion effects on the Big Five banks as well as on the National-city-rural banks not subject to Basel 3 accords.

By contrast, the feedback contagion effect from the banks to the offshore CNH market differ markedly between the Big Five banks and the National-city-rural banks.

Our results suggest that further movements in the offshore exchange markets, coming from off-shore news such as increasing trade frictions with the United States, will generate greater volatility in the Chinese banking sector and will call for greater macro and micro prudential regulation.

1 Introduction

This research examines the linkages between the off-shore fears, as illustrated by volatility in the CNH sport- exchange-rate markets, for the Chinese RMB w and on-shore financial market risk, captured by the realized daily range-volatility of Chinese banks.

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When we speak of banking-sector contagion effects, we first think of runs on bank deposits. When one bank experiences problems, there can be system-wide effects as depositors, with imperfect information, withdraw deposits at otherwise healthy banks. However, the issue of share-price volatility of banks has come to center stage with the Basel 3 accords focusing on capital-asset ratios. Banks are considered well capitalized if this ratio is above five percent and in need of intervention if the ratio falls below two percent. This increased volatility of a bank’s share price may lead to abrupt changes in the capital-asset ratio, leading to increased fears by depositors that the individual bank is not sufficiently capitalized, and subsequent withdrawals and bank runs.

Of course, banking-sector volatility often ties in with exchange-rate volatility. We have seen that banking crises, such as the Mexican Tequila crisis in the mid-1990’s and the Asian Flu in the late 1990’s, lead to abrupt exchange-rate depreciation and currency crises. However, otherwise stable banking sectors can become volatile following exchange-rate changes. In small open economies, for example, the liabilities of the banking sector are often in foreign currency while the assets are in local currency. Abrupt exchange-rate changes in times of a currency crisis can transform the balance sheet of bank from positive to negative, and thus destabilize the share price of the bank itself.

Thus, there are connections between overall banking stability and exchange-rate stability, or between currency and banking risks. Of course, instability in the banking sector has feedback effects on fiscal stability. In particular, when banks are in need of re-capitalization, often enough, governments have to run deficits, and increase their external indebtedness, which in turns leads to increased risk premia and volatility in exchange markets. As Reinhart and Rogoff (2013) note, banking-sector risks are equal-opportunity menaces, particularly for currency and bond markets.

The risks of a banking-sector crisis generating a currency crisis through a fiscal deficit and increased international borrowing in China is less likely since the central bank has abundant reserves. Moreover, the likelihood of a banking crisis leading to massive capital outflows is also less, due to the presence of controls on cross-border capital flows. However, these risks are not trivial. The increased banking-sector risk can generate pressures for increased currency speculation in offshore markets. At the same time, the volatility of the offshore RMB exchange market may also affect domestic banking sector stability in China. Better knowledge of how banking-sector and currency-market risks interact is crucial for understanding how to mitigate the contagion and magnifications effects of risks across markets and across borders. As Park and Shin (2018) note, there are many forms of contagion, with differing policy implications. This study examines the contagion and connectedness of Chinese banking with these offshore currency markets.

Using lower-frequency data, Gu and McNelis (2013) found that the off-shore CNH market was a key channel for transmitting volatility contagion effects from the Yen/Dollar spot market to on-shore Chinese financial markets, specifically in the RMB/Dollar spot market and the overall share price index. This study did not consider the share-price volatility of Chinese banks.
This study examines how developments in the off-shore CNH market, reflecting off-shore currency-market news, affect the volatility measures of key Chinese banks listed domestically. In turn, we also examine how changes in the volatility or risk measures of key banks have international repercussions through their feedback effects on volatility in the off-shore CNH market. More recently, Funke et al. (2015) examined the dynamic properties of this recently developed offshore RMB spot market differentials from the onshore RMB spot rates. However, Funke et al. (2015) did not examine the effects of these differentials on banking-sector stability in China, and how this market may be affected by bank share-price volatility in China.

We examine the intra-day volatility of a group of sixteen banks with data from August 2010 to the most recent dates. The data set includes the five largest banks, eight national-joint banks, and three city-rural banks. We also examine realized volatility from the CNH markets for the same time span.

In the next section we describe the data sets as well as the methodology we use for obtaining the realized daily volatility measures both for the banks as well as for the CNH offshore markets. The third section describes our empirical methodology and the key results of our investigation. We then contrast the results obtained at the start of our sample with those obtained during periods of external news or offshore fears with network graphics. The last section concludes.

2 Banking and CNH Markets: Volatility Measurement and Connectedness

2.1 Data

Table 2.1 gives the listing of the banks in our study. We follow the Ernst and Young classification, designating banks in three categories: the five largest, the national-joint stock banks, and the city-rural banks. We see that all of banks showed considerable volatility over the sample, between the starting state, Aug. 23, 2010, and the end date, January 11, 2019. In additional to the bank codes, we also number the banks from one through sixteen, with the CNH market being seventeen. This will facilitate interpretation of the network connections provided in the final section.

The realized daily range volatility measures, denoted by $\sigma_t^R$, come from an approximation based on spreads between the daily opening ($o$) and closing ($c$) , as well has maximum ($h$) and minimum ($l$) of the natural logarithmic values of the share prices observed each day. This approximation is based on Garman and Klass (1980):

$$\sigma_t^R = .511(h - l)^2 - .019[(c - o)(h - l - 2o) - 2(h - o)(l - o)] - .383(c - o)^2$$  

(1)
<table>
<thead>
<tr>
<th>No</th>
<th>Code</th>
<th>Name</th>
<th>EY Classification*</th>
<th>Center</th>
<th>Mean</th>
<th>Mean</th>
<th>Std Dev</th>
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<td>1</td>
<td>PAB</td>
<td>Ping An Bank</td>
<td>National-Joint Stock</td>
<td>Shenzhen</td>
<td>0.169</td>
<td>0.178</td>
<td>0.276</td>
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<td>2</td>
<td>BONB</td>
<td>Bank of Ningbo</td>
<td>City-Rural</td>
<td>Ningbo</td>
<td>0.123</td>
<td>0.054</td>
<td>0.406</td>
</tr>
<tr>
<td>3</td>
<td>SPDB</td>
<td>Shanghai Pudong Development</td>
<td>National-Joint Stock</td>
<td>Shanghai</td>
<td>0.126</td>
<td>0.036</td>
<td>0.311</td>
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<td>4</td>
<td>HX</td>
<td>Huaxia Bank Co.</td>
<td>National-Joint Stock</td>
<td>Beijing</td>
<td>0.102</td>
<td>0.108</td>
<td>0.248</td>
</tr>
<tr>
<td>5</td>
<td>CMBC</td>
<td>China Minsheng Bank Co</td>
<td>National-Joint Stock</td>
<td>Beijing</td>
<td>0.416</td>
<td>0.488</td>
<td>0.266</td>
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<td>6</td>
<td>ComBC</td>
<td>China Merchants Bank</td>
<td>National-Joint Stock</td>
<td>Shenzhen</td>
<td>0.160</td>
<td>0.023</td>
<td>0.354</td>
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<tr>
<td>7</td>
<td>BONJ</td>
<td>Bank of Nanjing</td>
<td>City-Rural</td>
<td>Nanjing</td>
<td>0.150</td>
<td>0.065</td>
<td>0.380</td>
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<td>8</td>
<td>IBC</td>
<td>Industrial Bank of China</td>
<td>National-Joint Stock</td>
<td>Fuzhou</td>
<td>0.222</td>
<td>0.251</td>
<td>0.275</td>
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<td>9</td>
<td>BOB</td>
<td>Bank of Beijing</td>
<td>City-Rural</td>
<td>Beijing</td>
<td>-0.003</td>
<td>-0.007</td>
<td>0.291</td>
</tr>
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<td>10</td>
<td>ABC</td>
<td>Agricultural Bank of China</td>
<td>Five Largest</td>
<td>Beijing</td>
<td>0.110</td>
<td>0.089</td>
<td>0.161</td>
</tr>
<tr>
<td>11</td>
<td>BOCOMM</td>
<td>Bank of Communications-Shanghai</td>
<td>Five Largest</td>
<td>Shanghai</td>
<td>-0.078</td>
<td>-0.060</td>
<td>0.181</td>
</tr>
<tr>
<td>12</td>
<td>ICBC</td>
<td>Industrial and Commercial Bank of China</td>
<td>Five Largest</td>
<td>Beijing</td>
<td>0.087</td>
<td>0.062</td>
<td>0.163</td>
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<td>13</td>
<td>CEB</td>
<td>China Evergright Bank</td>
<td>National-Joint Stock</td>
<td>Beijing</td>
<td>-0.018</td>
<td>0.039</td>
<td>0.201</td>
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<td>14</td>
<td>CCB</td>
<td>China Construction Bank</td>
<td>Five Largest</td>
<td>Beijing</td>
<td>0.163</td>
<td>0.040</td>
<td>0.202</td>
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<tr>
<td>15</td>
<td>BOC</td>
<td>Bank of China</td>
<td>Five Largest</td>
<td>Beijing</td>
<td>-0.006</td>
<td>-0.006</td>
<td>0.166</td>
</tr>
<tr>
<td>16</td>
<td>CITIC</td>
<td>China Citic Bank International</td>
<td>National-Joint Stock</td>
<td>Beijing</td>
<td>-0.032</td>
<td>-0.009</td>
<td>0.226</td>
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<tr>
<td>17</td>
<td>CNH</td>
<td>Hong-Kong China/US Dollar Spot Rate</td>
<td></td>
<td>Hong Kong</td>
<td>-0.045</td>
<td>-0.053</td>
<td>0.039</td>
</tr>
</tbody>
</table>

Range: 23 August 2010 to 11 January 2019

* Ernst and Young Classification
As noted by Yilmaz (2018), volatilities tend to have right skewness so one can approximate normality by taking the logarithms of the range volatilities. Figure 1 gives the median values of the realized volatility measures of these sixteen on-shore banks and the realized volatility of the off-shore CNH market. We see that at the time of the Euro Debt crisis at the beginning if the sample, there were closely related patterns of volatility. However in the middle of the sample and at the end of the sample, we see that the CNH market displayed greater volatility than the on-shore banks.

Given that the five largest banks have greater restrictions, due to Basel capital asset requirements, we compare the median values of these banks with the banks either publicly owned or owned by municipal governments, in Figure 2. They do not exhibit marked differences over the sample period.
2.2 Regularization of the big VAR model

As seen above, there are no appreciable differences in the median volatility measures between the five largest banks and the other banks in the sample. For this reason, we explore the connectedness or contagion patterns within and across the banking classes and with the CNH markets. Following a series of papers by Diebold and Yilmaz (2012), Diebold and Yilmaz (2013), Yilmaz (2018), we measure connectedness by making use of forecast-error variance decomposition matrices from VAR estimation. Since we make use of daily data, we use a lag length of five days and a forecast-error horizon of 20.

We apply the VAR model for the full sample but also make use of a rolling window of regressions of sample size 150, in order to estimate time-varying measures of connectedness. In addition to the 85 parameters for each variable in the VAR, representing the own-lag effects and the cross-lag effects for 15 variables with lag-length 5, we specify a constant term.

Given that the VAR model is a Big-VAR one, there is the need for regularization. We make use of the elastic net estimator due to Zou and Hastie (2005) for parameter reduction:

$$\beta_{Enet} = \min_{\beta} \left\{ \sum_{t=1}^{T} (y_t - \sum_{i} \beta_i x_{it})^2 + \lambda \sum_{i=1}^{k} \left[ (\alpha |\beta_i|) + (1 - \alpha)\beta_i^2 \right] \right\} \quad (2)$$

As noted by Yilmaz (2018), the elastic net combines the LASSO and Ridge penalties through the tuning parameters \(\{\alpha, \lambda\}\). With \(\alpha = 1, \lambda > 0\), it is a LASSO (Least Absolute Shrinkage Selection Operator), while it is a Ridge estimator with \(\alpha = 0, \lambda > 0\). With \(\lambda = 0\), there is no penalty for large numbers of parameters, and the estimates are least-squares.

Much like other more familiar criteria for reducing parameters by altering lag length, such as Akaike (AIC), Schwartz (BIC), and Hannan-Quinn (HQIC) information criteria, the elastic net penalizes models for having too many parameters. With this net, the choice of the regularization parameters \(\alpha, \lambda\) is the fundamental part. Selecting well is essential to the performance, since it controls the strength of shrinkage and variable selection, which, in moderation can improve both prediction and interpretability. However, if the regularization becomes too strong, important variables may be left out of the model and coefficients may be shrunk excessively, which can harm both predictive capacity and the inferences drawn about the system being studied.

We set the parameter \(\alpha = .5\), and estimate the coefficients of the model for alternative values of \(\lambda\). As \(\lambda\) increases, more and more parameters go to zero. One way to choose this parameter is to use a method based on cross validation, CV. In this approach, we select a grid of values for \(\lambda\), between \(\lambda = 0\), and \(\lambda^*\), the minimum \(\lambda\) which sets all of the coefficients \(\beta_i = 0\). We then select a set of out-of-sample Mean Squared Error measures, based on holding out 20% of the sample for each specified \(\lambda\) over the grid. We thus select the optimal \(\lambda\) as the one which minimizes the average out-of-sample mean squared error, based on
five sets of hold-outs of 20% of the data. We do this both for the full data set as well as for the smaller samples based on the rolling-window estimations.

We note that the coefficients \( \{\beta_i\} \) are based on the full in-sample elastic-net estimation based on the pre-specified tuning parameters, \( \alpha \), and the final optimal value of \( \lambda \), coming from the cross-validation method.

2.3 Variance decomposition and systemic risk

It is well known, of course, that the impulse-response paths and forecast error-variance decomposition measures are sensitive to the ordering of the variables in the VAR model. Following the approach of Diebold and Yilmaz (2012), we make use of the generalized method for obtaining forecast-error variance decomposition, due to Pesaran and Shin (1998), which does not rely on the Cholesky decomposition for orthogonal shocks.

This decomposition matrix is an asymmetric matrix, and serves as a measure of both the inward and outward connectedness of each variable in the model. In particular, off-diagonal measures tell us how much of the innovations in each variable can be accounted by the innovations in the other variables (inward connectedness) as well how much each variable contributed to the overall forecast error of the other variables (outward connectedness).

Diebold and Yilmaz (2014) have pointed out that this connectedness approach closely relates to measures of systemic risk. The inward-connectedness measure, they note, represents the exposures of individual banks to systematic shocks from the network as a whole, while the outward connectedness indicates the contribution of the individual bank to systemic network events [see Acharya et al. (2010) and Adrian and Brunnermeier (2016)].

Of course, we expect these measures of systemic risk to change through time, over the course of the sample, as changes take place in banking regulations and as financial markets become more open. For this reason we report these measures of systemic risk, not only for full sample, but also as time-varying measures based on rolling-window regressions.

3 Connectedness

As noted above we wish to examine the connectedness between the risk measures in the CNH market and the volatility of the banking system. We first examine the interactions between the CNH market and all of the Chinese banks. Then we look at the interactions between the CNH markets with the Big Five and with the National-City-Rural banks. Finally we examine the connectedness measures between the Big Five and the National-City-Rural
3.1 Full sample connectedness

Table 3.1 gives the measures of overall connectedness as well as connectedness from the CNH markets to the banking sector as a whole, as well as from the banking sector to the CNH markets.

<table>
<thead>
<tr>
<th></th>
<th>CNH to Banks</th>
<th>Banks to CNH</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.3614</td>
<td>0.8946</td>
</tr>
<tr>
<td>Big Five</td>
<td>0.2002</td>
<td>0.0765</td>
</tr>
<tr>
<td>National-City-Rural</td>
<td>0.1671</td>
<td>0.8184</td>
</tr>
</tbody>
</table>

What stands out in Table 3.1 is that the National-City-Rural banks have a much greater degree of connectedness with the CNH markets than the Big Five, but the direction of risk contagion is from the National-City-Rural banks to the CNH markets. For the full sample, the CNH market has a stronger effect on the Big Five than the National-City-Rural banks. There are thus asymmetric feedback effects, indicating that the National-City-Rural banks have more exposure or linkages to the offshore CNH market.

3.2 Time-varying connectedness

3.2.1 CNH market pressure on the banking system as a whole

Figure 3 makes use of all of the banks in the data set and shows the connectivity of the CNH to all banks in the system. We see that there is increased outward-connectivity to the banking system after 2011, when the US debt was downgraded from AAA, and at the time of the Greek debt crisis. In 2016, there was the Brexit vote, and following 2017, we see the increased volatility appeared at the same time when the trade frictions heightened between China and the US. Clearly the CNH markets transmit offshore risks to the Chinese banking system.

3.2.2 CNH market pressure on the Big Five and National-City-Rural banks

Figures 4 and 5 picture the outward connectedness between the CNH market volatility and the total volatility of the Big Five banks and the National-City Rural banks. We see little difference in the time pattern of the connectedness measures. The spikes take place at the beginning of the period, and after 2016, following Brexit and the beginning of the trade frictions between the United States and China. These measures indicate that the off-shore CNH market effectively transmits off-shore fears affecting the RMB to on-shore banking-sector risk, for both the Big Five and the National-City-Rural Banks in China.
3.2.3 Bank pressure on the CNH market

Figure 6 pictures the pressures from the Big Five banks to the CNH market. We see that it peaks in 2014, following a credit crunch in 2013. Figure 7 pictures the outward connectedness of two banks based in Shenzhen, Ping An Bank and the China Marchants Bank, on the CNH market volatility. We see that these two banks, located right next to the off-shore CNH market, explain, for some periods more than 90 percent of the volatility of this market. The effect of the Shenzhen banks diminishes only at the end of the sample, when the market has more outward effects on the Chinese banks than the Chinese banks have on this market.
Figure 5: Time-Varying Connectivity: CNH to National-City-Rural Banks

Figure 6: Time-Varying Connectivity: Big Five Banks to CNH Banks

Figure 7: Time-Varying Connectivity: Shenzhen Banks to CNH Markets
3.2.4 Network analysis

To better understand the changing dynamics of the connectedness among the banks and between the banks and the CNH market, we make use of network graphical analysis.

Figure 8 pictures the network links from estimation on the full data set. The numbers correspond to the bank numerical listing in Table 2.1 We see that Ping An Bank (1), based in Shenzhen, appears as a hub or key node. The CNH market, (17), based in nearby Hong Kong, appears to be at the periphery of the system, with its strongest links to nearby Ping An Bank. We also see that this bank has relatively strong links Shenzen-based China Merchants Bank (6), with Beijing-based banks CITIC (16), CEB (13), and BOB (9), and with Shanghai-based SPDB (3). Note that for the overall sample, the strongest links are among the National-City-Rural banks, not among the Big Five Banks. The strongest links from the Big Five (10, 11, 12, 15, 15) are with Ping An Bank.
Figure 9 pictures the network for December 20, 2016, following Brexit and the 2016 Presidential election. We see a different configuration. The CNH market (17) is now closer to the center of the system, while Ningbo-based BONB (2) and Beijing-based CITIC (16) appear to be at the hub of the system.
Figure 10 pictures the network connectedness for April 2018, when trade tensions with China were coming into play. Still another pattern of connectedness emerges. We see that node 17, for the CNH market, is directly linked to a larger number of banks, both to a Big Five bank, BOC (15), as well as to Shenzhen-based ComBC (6), Shanghai-based SPDB (3), BONB (2), IBC (8) in Fuzhou as well as CITIC (16) in Beijing. As trade frictions mounted between the USA and China in 2018, the CNH market became more closely linked with the transmission of risk across more regions of China as well as with one of the Big Five banks as well as the National-City-Regional banks.
4 Conclusion

The results of this paper show that the way the off-shore fears, signaled by volatility in the CNH Hong Kong spot market for the RMB-US Dollar, have become increasingly important sources of risk contagion for Chinese banks. The growing role of the CNH market not only has shown that it directly affects the risks of both large Big Five banks and National-City-Rural banks, not just in nearby Shenzhen but throughout the country. The risk measures also changes the pattern of contagion among domestic on-shore banks. Chinese banking-sector risks are not as insulated from off-shore fears reflected in currency-market volatility.

References


