Off-Shore Fears and On-Shore Risk: Exchange-Rate Pressures and Banking Contagion in China*

Jennifer Lai† and Paul D. McNelis‡

April 2019

Abstract

This paper assesses the effects of global uncertainty measures transmitted, through signals from the off-shore Hong Kong spot market for Chinese currency, listed as CNH, 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 (VARX) model estimation with machine-learning methods based on LASSO estimation. We use share-price volatility indices for 16 Chinese banks. For assessing off-shore fears, we make use of global uncertainty indices for trade and well as for the Chinese economy.

Our results show that off-shore measures of uncertainty directly affect the off-shore CNH market, which in turn affects the volatility of the on-shore banks, especially during times of heightened uncertainty about global trade or China. Thus the CNH market volatility is a leading indicator of on-shore Chinese banking-sector volatility.

By contrast, the feedback contagion effect from the banks to the off-shore CNH market differ markedly between the Big Five banks and the National-city-rural banks. When off-shore fears are low, only nearby Shenzhen banks directly affect the volatility of the off-shore CNH market.

Our results suggest that further movements in the off-shore 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. Far from being a shock absorber for the Chinese financial system, the CNH market appears to be a shock transmitter of risk from off-shore economic-policy uncertainty, to the Chinese banking system.

*The authors thank Iikka Korhonen, Laura Solanko, Zuzana Fungáčová, Riikka Nuutilainen, and Kun Huang of the Bank of Finland Institute for Transition Economies, and Cyn-Young Park and Peter Rosenkranz of the Asian Development Bank Research Department for comments on earlier drafts of this paper.

†School of Finance, Guangdong University of Foreign Studies, Guangzhou. Email: econlai@gmail.com

‡Gabelli School of Business, Fordham University, New York, N.Y. Email: mcnelis@fordham.edu

1 Introduction

This research examines the linkages between the off-shore fears, captured by movements in Economic Uncertainty indices, complied by Baker et al. (2016), and on-shore Chinese financial market risk, captured by the realized daily range-volatility of Chinese banks. We find that the key transmission channel of off-shore fears to on-shore banking sector risk and risk contagion, is the Hong-Kong based Chinese RMB spot market, CNH.

When we speak of banking-sector contagion effects, we naturally 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 off-shore markets. At the same time, the volatility of the off-shore 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 off-shore risks, through these off-shore 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 and responding to off-shore uncertainty, 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 off-shore RMB spot market differentials from the on-shore 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 or global measures of economic policy uncertainty.

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, as well as normalized Economic Policy Uncertainty (EPU) indices obtained from Baker et al. (2016).

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 off-shore 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 off-shore fears with network graphics. The last section concludes.

2 Uncertainty, CNH Markets and Bank Volatility

2.1 Data

Table 1 gives the normalized mean, median and standard deviations of the Economic Policy Uncertainty (EPU) indices as well as the VIX between Dec. 2010 and Dec. 2018. All the data are normalized between [0,1], with x*(i) = [x(i)-min(x)]/[max(x)-min(x)] replacing the original x-data.

We also list the dates when the max and min values occurred in the sample. Baker et al. (2016) compile these indices from scans of ten major newspapers in the United States for category-specific polices combined with the word un-

Table 1: Normalized Global Uncertainty Indices and VIX: 2010-2018

					Dates of Uncertainty	
No.	Index	Mean	Median	Std Dev	Max	Min
1	Econ Pol	0.272	0.233	0.150	Aug-11	Aug-15
2	Monetary	0.206	0.165	0.141	Aug-11	Oct-18
3	Fiscal	0.292	0.235	0.180	Aug-11	Aug-15
4	Taxes	0.290	0.236	0.175	Dec-12	Aug-15
5	Spending	0.189	0.127	0.165	Aug-11	Aug-15
6	Health	0.320	0.280	0.170	Oct-13	Aug-15
7	Nat. Sec	0.365	0.326	0.194	Dec-18	Feb-18
8	Entitlements	0.299	0.238	0.189	Aug-11	Aug-15
9	Regulation	0.263	0.217	0.149	Oct-10	Feb-18
10	Fin. Reg.	0.236	0.184	0.162	Oct-11	Aug-15
11	Trade	0.190	0.131	0.171	Jul-18	Aug-15
12	Sov. Devt/Currency Crisis	0.170	0.110	0.155	Aug-11	Dec-18
13	China	0.249	0.218	0.155	Dec-18	May-11
14	3-Component	0.239	0.212	0.129	Aug-11	Feb-18
15	Global Policy	0.247	0.223	0.134	Aug-11	Aug-14
16	VIX	0.189	0.154	0.141	Aug-11	Nov-17

certainty. They note that there is a correlation between their measure of uncertainty and stock-market uncertainty, as captured by the VIX, the implied volatility from options on the Standard and Poor 500 stock index. They also point out that their uncertainty measure is based on policy uncertainty, while the VIX is based on overall uncertainty.

The data used in Baker et al. (2016) were monthly. Instead of interpolation for daily observations, we made use of the method of Chow and Lin (1971), using daily observations on the VIX to forecast the daily observations on EPU indices. Thus our EPU indices capture information from the VIX as well as from the initial sample obtained from Baker et al. (2016).[1]

We see that the highest periods of US policy uncertainty took places earlier in the sample, with the exception of uncertainty over National Security policy and Trade policy, which took place in Dec. 2018. The loss of confidence in US National Security at that time was due, not surprising, to the impending crisis of a prolonged government shutdown. The second index peaked in December 2018 after President Trump called himself "Mr. Tariff Man". However, for the other indices, the period form 2015 to 2018 saw reduced levels of uncertainty. For China, the peak value for uncertainty was in December 2018. It was at this time that two Canadian citizens were detained in mainland China.

Although all of the indices, by definition, have maximum values of unity, the mean values have values ranging from .17 to .36. Thus, periods of maximum uncertainty are far above the mean values of the indices.

[1] **?** make use of the VIX for evaluating movements in the RMB, but they find this variable is less important after Aug. 2015.

Figure 1: Indices of Policy Uncertainty

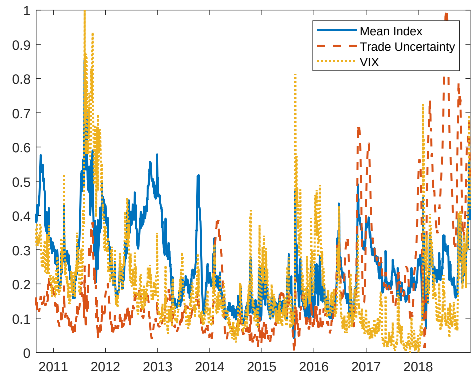


Figure 1 pictures the mean of the normalized indices, as well as the index of global trade uncertainty and the VIX. The solid curves represent the mean values of all of the indices, the broken curve, the index of trade uncertainty, and the dotted curve is the VIX.

We see that most of the volatility of the mean values takes place at the beginning of the sample. However, the trade uncertainty values and volatility increase at the end of the sample The VIX shows high volatility both at the beginning and end of the sample. We also see increases in the mean values of the mean index and the VIX in 2016. This is the beginning of the prolonged BREXIT process.

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 normalize the share price indices with a starting value of unity for each bank, and then take the logarithmic values. Thus the mean and median values represent percentage net expected gains or losses since the start of the sample. We see that all of banks showed considerable volatility over the sample, between the starting state, December 2010, , and the end date, December 2018. 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 σ_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):

$$\sigma_t^R = .511(h-l)^2 - .019[(c-o)(h-\hat{l}-2o) - 2(h-o)(l-o)] - .383(c-o)^2 \tag{1}$$

Table 2: Chinese Bank Share and CNH Rates

No	Code	Name	EY Classification*	Center	Normalized Data Mean	Median	Std Dev
1	PAB	Ping An Bank	National-Joint Stock	Shenzhen	0.169	0.178	0.276
2	BONB	Bank of Ningbo	City-Rural	Ningbo	0.123	0.054	0.406
3	SPDB	Shanghai Pudong Development	National-Joint Stock	Shanghai	0.126	0.036	0.311
4	HX	Huaxia Bank Co.	National-Joint Stock	Beijing	0.102	0.108	0.248
5	CMBC	Chinga Minsheng Bank Co	National-Joint Stock	Beijing	0.416	0.488	0.266
6	ComBC	China Merchants Bank	National-Joint Stocl	Shenzhen	0.100	0.023	0.354
7	BONJ	Bank of Nanging	City-Rural	Nanjung	0.150	0.065	0.380
8	IBC	Industrial Bank of China	National-Joint Stock	Fuzhou	0.222	0.251	0.275
9	BOB	Bank of Beijing	City-Rural	Beijing	-0.003	-0.007	0.291
10	ABC	Agricultural Bank of China	Five Largest	Beijing	0.110	0.089	0.161
11	BOCOMM	Bank of Communicatins-Shanghai	Five Largest	Shanghai	-0.078	-0.060	0.181
12	ICBC	Industrial and Commercial Bank of China	Five Largest	Beijing	0.087	0.062	0.163
13	CEB	China Evergright Bank	National-Joint Stock	Beijing	-0.018	0.039	0.201
14	CCB	China Construction Bank	Five Largest	Beijing	0.103	0.040	0.202
15	BOC	Bank of China	Five Largest	Beijing	-0.006	-0.006	0.166
16	CITIC	China Citic Bank International	National-Joint Stock	Beijing	-0.032	-0.009	0.226
17	CNH	Hong-Kong China/US Dollar Spot Rate		Hong Kong	-0.045	-0.053	0.039

Range: 23 August 2010 to 11 January 2019

* Ernst and Young Classification

Figure 2: Chinese Banking and off-shore CNH Range Volatilities

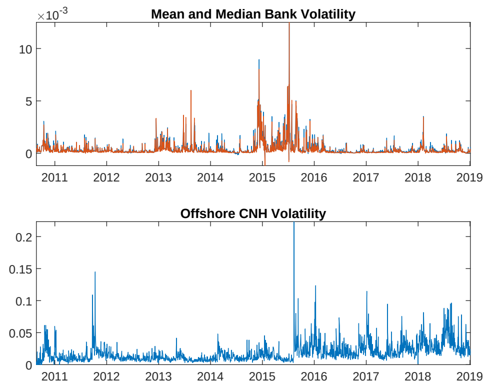
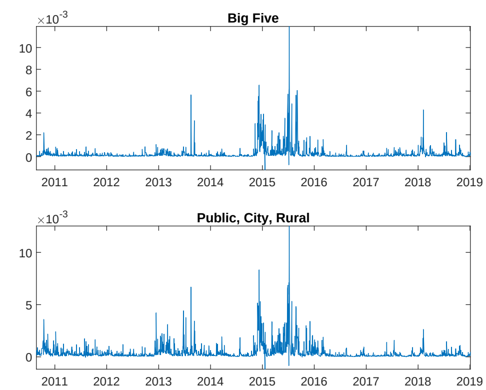


Figure 3: Median Range Volatilizes Big Five and Public-City-Rural Banks



As noted by Yilmaz (2018), volatilities tend to have right skewness so one can approximate normality by taking the logarithms of the range volatility.

Figure 2 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 3. They do not exhibit marked differences over the sample period.

2.2 Regularization of the big VAR-X 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-X 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 and a set of 15 control variables, representing the EPU indices in Table 1.

Given that the VARX model is a Big-VARX one, there is the need for regularization. We make use of the Elastic Net (EN) estimator due to Zou and Hastie (2005) for parameter reduction or regularization:

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

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), it is a Ridge estimator with $\alpha = 0$,$\lambda > 0$. With $\lambda = 0$,of course, there is no penalty for large numbers of parameters, and the estimates are least-squares.

The OLS estimator, with no penalty for large numbers of parameters, would allow for large numbers of small, insignificant cross-effects and thus overstates degrees of connectedness among the dependent variables in the VAR-X model. By making use of the Elastic Net, we are minimizing the degree of inter connectedness among the variables, by eliminating variables which have small absolute or squared values. Thus, when we do find inter connectedness, it

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 α, λ 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 interpret ability. 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 λ. As λ 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 λ, between $\lambda = 0$,and λ^*, the minimum λ 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 λ over the grid. We thus select the optimal λ 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 per-specified tuning parameters, α, .and the final optimal value of λ, .coming from the cross-validation method. We estimate the coefficients in three steps:

1. specify α =.5 for the elastic-net estimation, as a fixed hyper-parameter;
2. full sample elastic-net estimation with various λ;
3. cross validation with various λ;
4. choose the optimal result based on the average mean-squared out-of-sample errors.

.

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

Table 3: Elastic Net Estimates of Uncertainty Indices

	Trade Policy	China News
PAB	0.0000	-0.0002
BONB	0.0000	0.0000
SPDB	0.0000	-0.0001
HX	0.0000	-0.0002
CMBC	0.0000	-0.0001
ComBC	0.0000	0.0000
BONJ	0.0000	-0.0002
IBC	0.0000	-0.0003
BOB	0.0000	0.0000
ABC	0.0000	0.0000
BOCOMM	0.0000	0.0000
ICBC	0.0000	0.0000
CEB	0.0000	0.0000
CCB	0.0001	0.0000
BOC	0.0000	0.0000
CITIC	0.0000	0.0000
CNH	**0.0092**	**0.0047**

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

Before discussing connectedness with the Forecast Error Variance Decomposition, we briefly discuss the Elastic Net estimates. In particular, our results show that only two of the EPU indices were not driven to zero, the index for Trade Uncertainty and the index for China News Uncertainty. The non-zero effects of these variables fell mostly on the CNH volatility, with some minor effects on a few banks such as IBC,BONJ, and HX. The results appear in Table 3.

For all of the estimated coefficients of the model, 1496, only 293 were non-zero. The Elastic Net machine learning, based on the optimal out-of-sample criterion for the penalty term for λ,ruthlessly enforced parsimony on the model.

Table 4: Inward, Outward and Net Connectedness: Full Sample

	Inward	Outward	Net
PAB	0.291	7.137	**6.846**
BONB	0.667	2.885	**2.218**
SPDB	0.845	0.360	-0.485
HX	0.949	0.368	-0.581
CMBC	0.857	0.340	-0.517
ComBC	0.915	0.167	-0.748
BONJ	0.863	0.402	-0.461
IBC	0.989	0.034	-0.955
BOB	0.956	0.083	-0.874
ABC	0.753	0.854	**0.102**
BOCOMM	0.951	0.311	-0.639
ICBC	0.644	0.083	-0.562
CEB	0.933	0.129	-0.804
CCB	0.974	0.097	-0.877
BOC	0.923	0.063	-0.860
CITIC	0.896	0.028	-0.868
CNH	0.025	0.091	**0.066**

Table 4 gives the inward and outward connectedness measures of the banks as well as the CNH market for the full sample. The inward measure is the percentage of total variance can be explained by shocks from the other banks. By definition, the maximum value of this is 1. We see that for some banks, such as HX, BOB, ComBC, CCB, and BOC, a considerable proportion, more than 90 percent, of their volatility is due to systemic risks from other banks. For outward volatility, this is the amount of variation of the other banks' total volatility which is due to the specific bank in question. We see that only three banks, PAB, BONB, and ABC, are net transmitters of risk to the rest of the system. We also see that the CNH market is also a net transmitter of risk, but to a far lower degree that the PAB and BONB banks.

Table 3.1 gives the measures of connectedness between the CNH market and the total banking system as well as to the three categories of banks. W

Table 5: Full Sample Measures of Connectedness

	CNH to Banks	Banks to CNH
All	0.025	0.090
Big Five	0.009	0.013
National	0.013	0.045
City-Rural	0.000	0.014

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 Banks to the

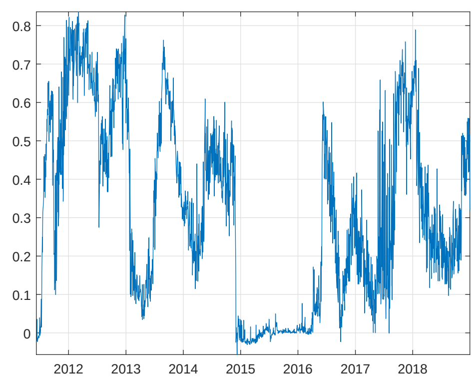
CNH markets. For the full sample, the CNH market has a stronger effect on the National Banks than on the Big Five and practically no effect on the City-Rural Banks..

3.2 Time-varying connectedness

3.2.1 CNH market pressure on the banking system as a whole

Figure 4 shows the net connectivity of the CNH to all banks in the system with a following window estimation. 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 off-shore risks to the Chinese banking system at key periods of uncertainty.

Figure 4: Time-Varying Connectivity: CNH to Banks



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

Figures 5 pictures the net outward connectedness between the CNH market volatility and the total volatility of the Big Five, National and City Rural banks. We see little difference in the time pattern of the connectedness measures. All three are relatively large at the start of the sample and at the end of the sample. The only difference we not is that the National and City-Rural Bank volatility measures response slightly before the Big Five banks in 2016.

Figure 5: Time-Varying Connectivity: CNH to Classes of Banks

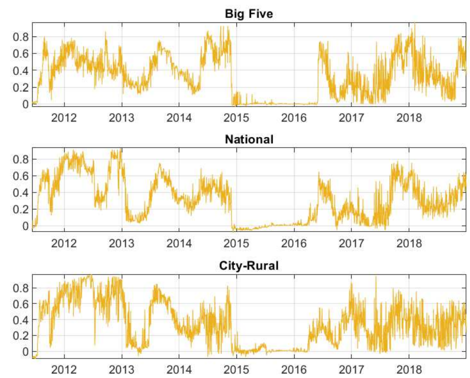
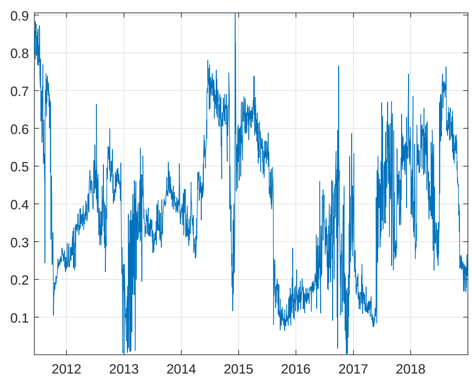


Figure 6: Time-Varying Connectivity: All Banks to CNH Markets



3.2.3 Bank pressures on the CNH market

Figure 6 pictures the pressures from all of the banks to the CNH market. We see that it peaks in 2014, following a credit crunch in 2013. However there is large drop in the influence of the on-shore banks in 2015. **?** note that after August 2015, the People's Bank of China used the deviation of the off-shore rate from the on-shore central parity and a US dollar index as the key variables for determining the central parity. In short, the off-shore exchange rate became an active policy

Figure 7 pictures the pressures from the three-classes of banks to the CNH market. This figure shows that the the National Banks have a greater effect on the CNH market than the Big Five or the City-Rural banks. We see a drop in their connectedness to the CNH markets after 2015. We also see, toward the end of the sample, as the Trade Index becomes more important, the effects

Figure 7: Time-Varying Connectivity: Classes of Banks to CNH

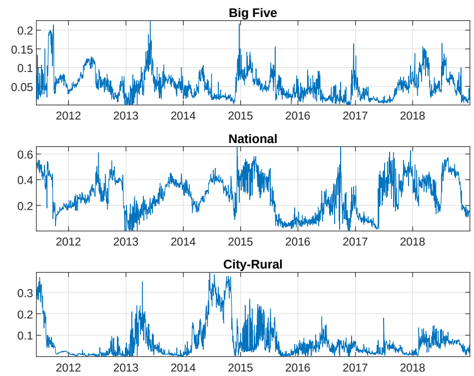
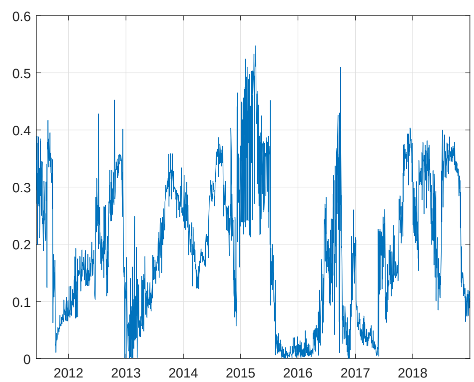


Figure 8: Time-Varying Connectivity: Shenzen Banks to CNH



of on-shore banks, of any type, become less important for the CNH market volatility.

Of course, geography also plays a role. Figure 8 pictures the time-varying effects on the CNH market volatility. We see the same drop in volatility after 2015. We also see that the effects of the Shenzen banks, both of which are classified as National banks, account for most of the influence of this class of on-shore banks on the CNH market.

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 4 shows the net connectivity of the CNH to all banks in the system with a rolling window estimation. 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 off-shore risks to the Chinese banking system at key periods of uncertainty.

Figure 9: Network Connectedness: Full Estimation

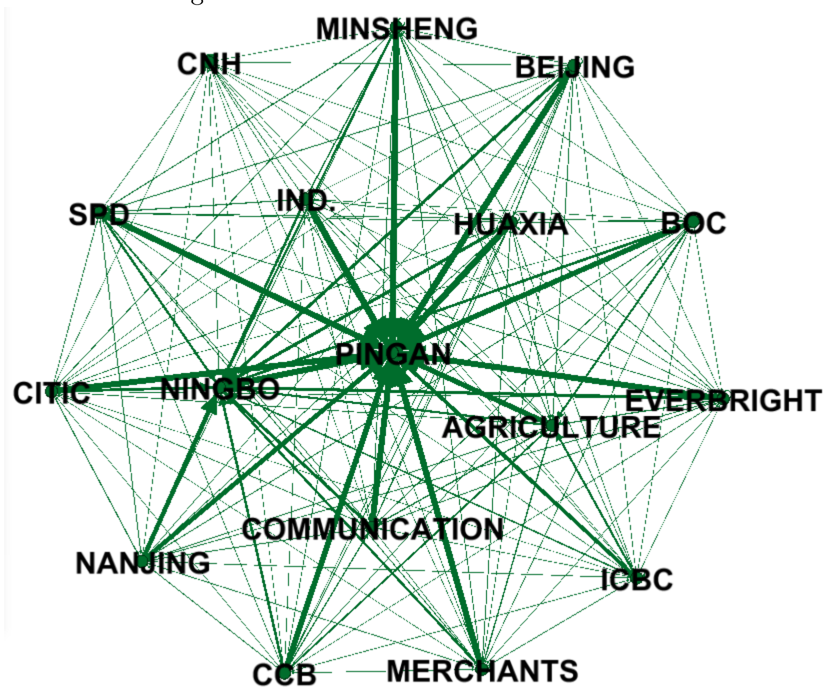
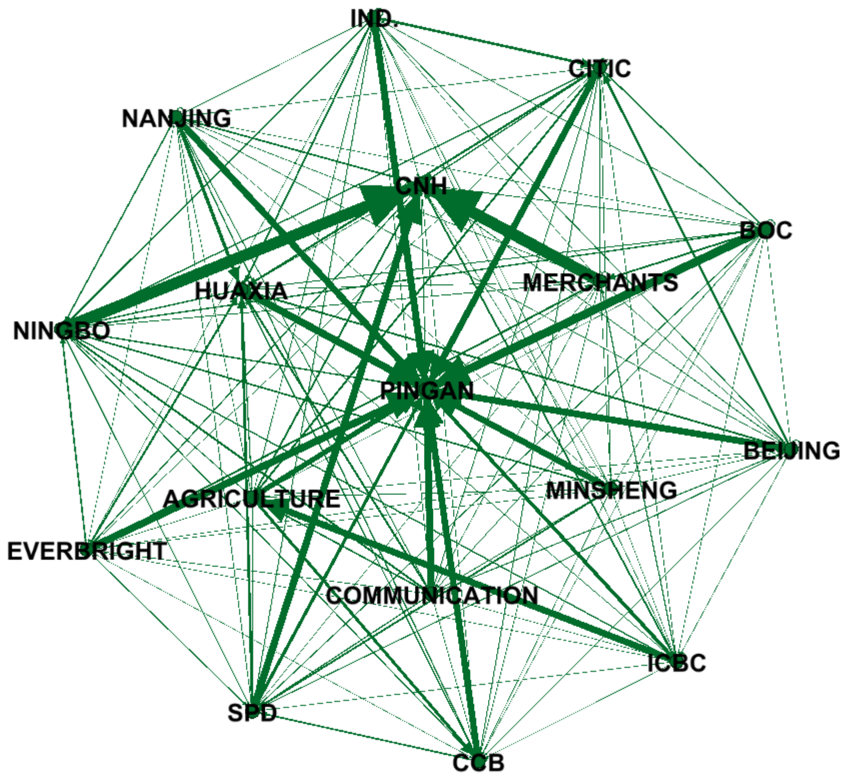


Figure 10 pictures the network for March 2017, following Brexit and the 2016 Presidential election. We see a different configuration. The CNH market is now closer to the center of the system, with connectedness to Ningbo-based BONB and Beijing-based Merchants.

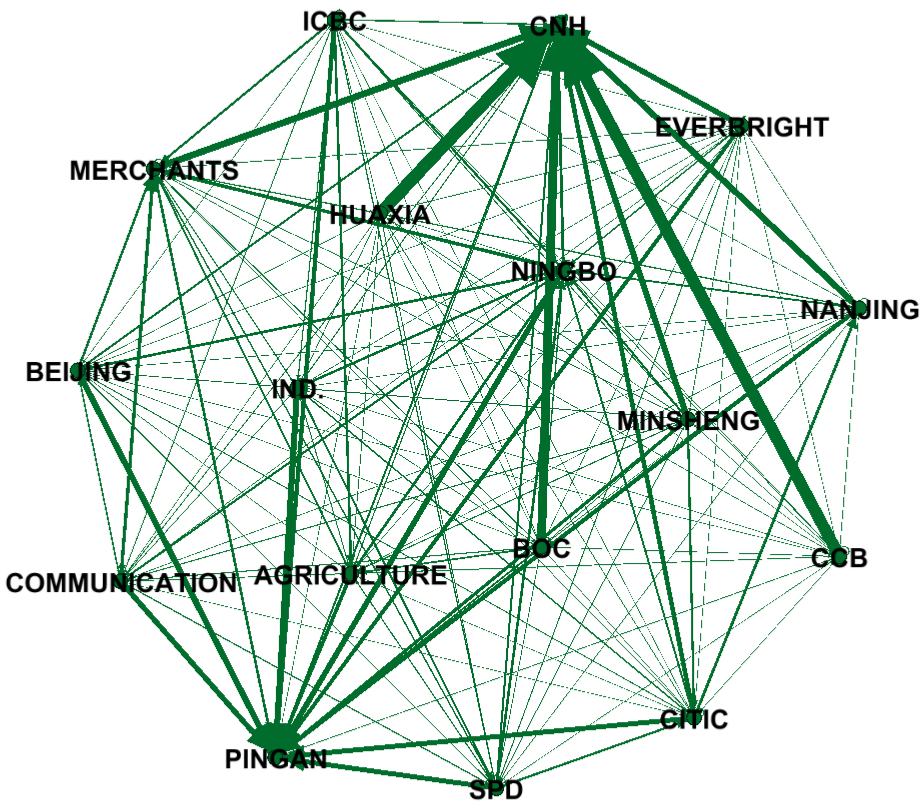
Figure 10: Network Connectedness: March2017



Net

Figure 11 shows that the CNH market, has more and even stronger connections with many more banks in the network.

Figure 11: Network Connectedness: December 2018



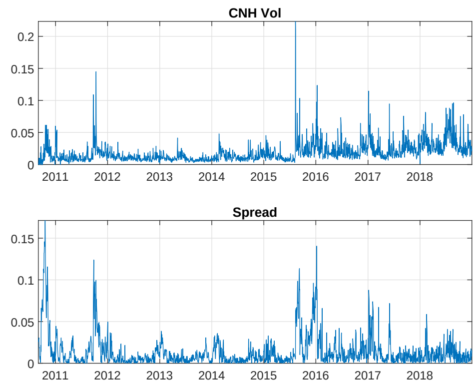
The network analysis shows that as time moved on, the CNH market became a more central and critical element in understanding the network links among the banking sector in China.

4 Robustness: CNH Volatility or CNH-CNY Spread?

Funke et al. (2015) drew attention to the important of the differential between the off-shore CNH and the on-shore CNY markets for Chinese financial markets. What matters more, the volatility of the off-shore market, or the differential between the off-shore and on-shore markets?

12 pictures the CNH range volatility and the absolute value of the spread between the off-shore CNH and the on-shore CNY market. This figure shows little difference. The peak periods of volatility correspond closely to the peak periods of the Spread.

Figure 12: CNH Volatility and Off-Shore/On-Shore Spread



4.1 Full period estimation with CNH-CNY Spread

For the overall sample, we find that the EPU index for financial liberalization is the most important control variable, rather than the EPU indices for trade policy or China. As in the case of the volatility measure, this control variable only affects the Spread variable.

Table 6 gives the inward, outward, and net connectedness measures for full sample estimation when we use the CNH-CNY spread rather the range volatility. We see little or no difference between this table and Table 4. The banks having the strongest net outward connectedness measures remain PAB and BONB. The influence of the Spread between the off-shore and on-shore markets appears to be smaller in absolute value, and now negative, relative to the influence of the range volatility of the off-shore market.

4.2 Time-Varying Connectedness with CNH-CNY Spread

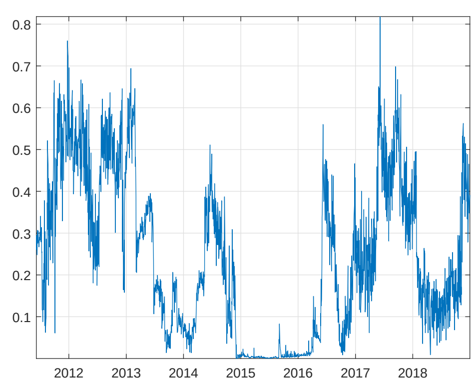
Figure 13 pictures the time-varying measure of outward connectedness from the CNH-CNY spreads to banks. We see very similar patterns to those in Figure 4. The importance of the spreads are largest at the beginning of the sample and at the end, both at the time of Brexit and at the time of the trade tensions between the US and China.

The results of this robustness check indicate that little differences show up if we use the volatility of the off-shore market or the spread between the off-shore and on-shore market as our measure of exchange-rate pressure on Chinese banks.

Table 6: Connectedness under Full Sample with CNH-CNY Spread

	Inward	Outward	Net
PAB	0.304	7.159	6.855
BONB	0.664	2.886	2.222
SPDB	0.839	0.419	-0.420
HX	0.942	0.420	-0.521
CMBC	0.861	0.340	-0.521
ComBC	0.914	0.159	-0.755
BONJ	0.864	0.412	-0.452
IBC	0.981	0.040	-0.942
BOB	0.957	0.076	-0.881
ABC	0.752	0.830	0.077
BOCOMM	0.955	0.286	-0.669
ICBC	0.664	0.101	-0.563
CEB	0.938	0.128	-0.810
CCB	0.971	0.100	-0.871
BOC	0.928	0.062	-0.866
CITIC	0.898	0.027	-0.871
CNH	0.028	0.014	-0.014

Figure 13: Time-Varying Connectivity: CNH to Banks, with CNH-CNY Spread



5 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, or by spreads between the off-shore and on-shore RMB markets, 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 change 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.

The key policy implication is that overall banking share-price volatility is not as insulated from rest of the word as one may imagine, in the presence of limited capital mobility. In this process of gradual financial opening, the development of the more-flexible CNH markets represents a further step in the internationalization of the RMB. But is it flexible enough? Or do discrepancies between the on-shore and off-shore markets simply magnify uncertainty for the financial system as a whole. While Friedman (1953) extolled the benefits of flexible exchange rates, it was in the context of a unified exchange-rate system, not a dual system with on-shore and off-shore markets. Our conjecture is that a more flexible RMB could function as an effective shock absorber for the financial system when the off-shore and on-shore markets are integrated.

References

Acharya, V., L. Petersen, T. Philippe, and M. Richardson (2010). Measuring systemic risk. Technical report, New York University.

Adrian, T. and M. Brunnermeier (2016). Covar. *American Economic Review*.

Baker, S., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics 131*(4), 1593–1636.

Chow, G. and A. Lin (1971, November). Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *Review of Economics and Statistics 53*(4), 372–375.

Diebold, F. and K. Yilmaz (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting 28*(1), 57–66.

Diebold, F. and K. Yilmaz (2013). Measuring the dynamics of global business cycle connectedness. Pier working paper archive, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania.

Diebold, F. X. and K. Yilmaz (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*.

Friedman, M. (1953). *Essays in positive economics*, Chapter The case for flexible exchange rates, pp. 157–203. University of Chicago.

Funke, M., C. Shu, X. Cheng, and S. Eraslan (2015). Assessing the CNH and CNY pricing differential: Role of fundamentals, contagion and policy. *Journal of International Money and Finance 59*(C), 245–262.

Garman, M. and M. Klass (1980). On the estimation of security price volatilities from historical data. *Journal of Business*.

Gu, L. and P. McNelis (2013). Yen/dollar volatility and Chinese fear of floating: Pressures from the ndf market. *Pacific-Basin Finance Journal 22*(C), 37–49.

Park, C. and K. Shin (2018). Global banking network and regional financial contagion. Technical report, Asian Development Bank.

Pesaran, H. H. and Y. Shin (1998, January). Generalized impulse response analysis in linear multivariate models. *Economics Letters 58*(1), 17–29.

Reinhart, C. M. and K. S. Rogoff (2013). Banking crises: An equal opportunity menace. *Journal of Banking & Finance 37*(11), 4557–4573.

Yilmaz, K. (2018, March). Bank Volatility Connectedness in South East Asia. KoÃ§ University-TUSIAD Economic Research Forum Working Papers 1807, Koc University-TUSIAD Economic Research Forum.

Zou, H. and T. Hastie (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*.