Shifting Balances of Systemic Risk in the Chinese Banking Sector: determinants and trends[⋆]

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Abstract

We examine the evolution and factors of systemic risk in the Chinese banking sector over the last decade from the perspective of domestic and international investors. We apply the SRISK measure of systemic risk to a representative sample of listed Chinese institutions that captures up to 60% of total banking assets and utilize the Granger-causality network-based approach to demonstrate interlinkages among Chinese banks beyond the largest financial institutions. We show a dramatic increase in systemic risk after 2011 and the increased contribution of small- and medium-sized banks. We also identify causal relationships from housing prices, economic policy uncertainty and shadow banking towards systemic risk and from shadow banking to housing prices. According to our results, the concerns from both domestic and international investors about the stability of the Chinese banking system are well justified and a systemic event could be caused by distress in a Chinese financial institution outside the group of the largest banks.

Keywords: Systemic Risk, Chinese Banking sector, Interconnectedness, Economic Policy Uncertainty, Shadow Banking

JEL Codes: G01, G18, G21, E50

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1. Introduction

Effective monitoring and control of risks inherited in the financial system and its resilience to shocks received renewed attention in the aftermath of the Global Financial Crisis of 2008. The ongoing regulatory reform process is still far from over and the adequacy of proposed and implemented financial regulations is subject to heated debate among academics, institutions and practitioners (IMF (2018)). Unresolved issues on the post-crisis regulatory reform agenda, adverse feedback loops from volatility in global equity markets on global financial stability, and the buildup of vulnerabilities via risk taking in credit allocation have drawn renewed attention to the importance of internationally coordinated systemic risk assessment and timely policy responses. The efficiency and scope of the existing regulatory mechanisms remains under dispute, since they have not been crisis-tested and hence their effectiveness remains highly uncertain. Although the contribution of the US and the EU banking institutions to global systemic risk tends to dominate the ongoing debate, increasing attention has been paid to their Chinese counterparts, as the large-scale and opaque interconnections of the Chinese financial system is considered to pose stability risks (Williams (2018)).

In this paper, we provide evidence that systemic risk in the Chinese banking sector should be a major source of concern for international and domestic investors. We apply the SRISK measure of Brownlees and Engle (2016) to estimate the systemic risk of Chinese banks as an institution's capital shortfall in response to a shock in domestic or international equity markets. The domestic market is proxied by The Datastream Domestic China Index, while for international markets we use the MSCI Emerging Markets index (MSCI EM) as benchmark. Given the critical role of China in global markets, a pronounced domestic shock is likely to translate into an international one and vice versa. Thus, the MSCI EM Index can be an appropriate benchmark for an international investor in emerging markets. Our approach is similar to Engle et al. (2014), who examine systemic risk contributions of European banks at a global and domestic level. By using a global benchmark, Engle et al. (2014) identify global systemically important financial institutions in case of an international shock and investigate the impact of the rescue of a firm on the domestic economy.

We show that the propensity of Chinese banks to be undercapitalized when the market as a whole is undercapitalized increased dramatically in recent years, justifying concerns of domestic and international investors and policymakers about market stability. We find that financial institutions smaller than the four biggest banks have become important contributors of systemic risk, in terms of both individual contribution and their effect on the riskiness of other banks. We complement the SRISK results with the Granger-causality network-based approach of Billio et al. (2012) to demonstrate the extensive interlinkages among banks. The relatively smaller banks are more interconnected than the largest banks and those linkages have the potential to act as channels of risk spreading from one institution to another. According to our results, smaller banks have become net contributors of systemic risk and both their absolute and relative importance as well as influence in the financial system have increased in recent years.

A main contribution of the paper is that we credibly identify economic policy uncertainty, shadow banking and real estate prices as contributing factors to the increase in systemic risk. A series of vector error correction models show robust uni- and bi-directional causal relationships, both in the long- and the short-run, where SRISK is typically influenced by the Economic Policy Uncertainty index of Baker et al. (2016), the Chinese real residential property price index and two proxies of shadow banking developed in Sun (2019), a traditional measure based on credit creation and a more general measure of money creation by banks based on accounting statements. In addition, we demonstrate a causal relationship from the shadow banking proxies towards the property price index. This is one of the few empirical results that relate directly the rise in shadow banking to the rise in the real estate prices in China during recent years. We identify the increase in the real estate prices, economic policy uncertainty and the rise in shadow banking as potential sources of an increase in systemic risk and conclude that the influence of shadow banking on the systemic risk of the banking sector to be both direct and indirect via the housing market.

Our main policy suggestion is that the regulatory reforms in the Chinese banking sector must focus not only on the largest banks but on smaller institutions as well. A series of bank insolvencies and government bailouts of banks in recent years[1] highlight the increased

[1]Some prominent examples after 2013 include financial institutions such as Dalian, Langfang, Inner Mongolia, Jiangxi, Shanxi Qinnong, Jinzhou, Heng Feng, Fuxin and Baoshang.

vulnerability of regional banks. We show that a larger number of banks have become more interlinked and carry more clout, which may have important implications for the portfolio diversification strategies of investors. Any government interventions should take into account the complex interactions between policy uncertainty, shadow banking, systemic risk and the real estate market, where systemic risk appears to be the recipient and, sometimes, the distributor, of influence.

2. The financial system and systemic risk in China

2.1. Post-2008 crisis developments

It was apparent from the onset that the massive RMB 4 trillion stimulus program, announced by the Chinese government shortly after launching the policy of monetary easing in September 2008, would be channeled to the economy through increased bank lending. As a result, in a relatively short period of time, the assets of Chinese banks increased dramatically from 98% in 2007 to 109% of GDP by 2010 for the big four banks, and from 82% in 2008 to 103% of GDP by 2010 for the smaller state-owned banks. The overall assets of the Chinese banks reached USD 39.3 trillion, or around 310% of GDP by 2017 (OECD (2018)). Taking into account the off-balance sheet exposure of banks increases the figure to 387% of GDP in 2017. Notably, with debt of less than 15% of GDP, relative to 120% of GDP in the United States at the onset of the 2008 financial crisis, Chinese financial institutions were largely unaffected by the credit flow disruptions experienced in advanced industrial countries and were in a strong position to increase the supply of credit (Lardy and Subramanian (2011)).

Credit growth tends to be a powerful predictor of financial crises and China is unlikely to be an exception, given the magnitude and speed of its credit boom (Chen and Kang (2018)). China's financial system appears to have all the salient characteristics of a system liable to a crisis such as high leverage, maturity mismatches, credit risk and opacity. The large-scale and opaque interconnections of the Chinese financial system have been emphasized as a continuing threat to the economic stability of the country (IMF (2018)). In particular, the likely transfer of risks across markets and sectors due to the links of Chinese banks to the shadow banking sector and products through their off-balance sheet exposure has recently received a lot of attention (Ehlers et al. (2018)). Preventing and controlling risks, as well as gradually transferring the off-balance sheet capital to the balance sheet due to tightened regulation, has become one of the key priorities of Chinese banks in the past few years. Recognizing the threats of the shadow banking system, as well as other factors such as a housing bubble, contingent debt of local governments, and their heavy reliance on land sales for financing, People's Bank of China (PBOC) advisers warned that China could face highly probable but neglected financial risks (so-called gray rhino[2]), reflecting potential threats for the Chinese economy, and proposed measures including direct bailouts of enterprises and bank recapitalization should a crisis hit (Bloomberg News (2018)).

There is consensus that the Chinese banking sector is subject to systemic risk, yet its sources and magnitude have not been thoroughly assessed. According to Gang and Qian (2015), monetary policy shocks significantly increased systemic risk in the Chinese financial system between October 2008 and November 2013 but had only a limited effect on the real economy. Chen and Du (2016) argue that, similarly to the US and the EU, financial innovations in China are related to bank stability. Non-performing loans are another potential source of risk, since banks that are more exposed to bad loans are likely to take excess credit risk to cover their losses. This behavior of bank managers may temporarily alleviate the problem of non-performing loans but is likely to increase moral hazard and cause greater losses in the long run due to deterioration in the loan portfolio and institutional stability (Zhang et al. (2016)). Spillover effects have also been considered as a prime facilitator of systemic risk in the banking sector (Xu et al. (2018)). Using a network-based approach, Sun (2020) finds that contagion risk among banks from the default of a single institution is negligible but the network amplification effect of the losses is significant. In a network setup, spillover effects are the main driving factor for bank-specific counterparty risk. Fang et al. (2018) argue that institution size is positively related to systemic risk, indicating that firms

[2]The stress tests conducted by Chinese regulators in early 2014 included a scenario involving banks absorbing losses of 30% on on- and off-balance sheet wealth management products (WMPs) invested in credit assets (though excluding products invested in bonds and deposits). Only one bank's capital adequacy ratio fell below 9% (People's Bank of China (2014)). Nevertheless, the channel operations surged dramatically in the subsequent years, so the risks are likely to increase further.

with higher market capitalization are more systemically important. However, large banks in China will almost certainly be bailed out by the government during a distress, which lowers their risk contributions during the crisis. This is again consistent with moral hazard, where too-big-to-fail firms accumulate excess risk, knowing that they will receive government support in the case of a capital shortfall.

2.2. Shadow banking and the real estate market in China

The issue of shadow banking in China has received significant attention in the recent literature. A key result comes from Lai and Van Order (2019), who identify a relationship between shadow banking, proxied by loans from non-banking financial institutions, and house prices using Pooled Mean Group estimation in 65 Chinese cities. The authors find that house prices grow faster with availability of shadow banking funds, which increased rapidly over the 2006 - 2015 period. This provides empirical support to our hypothesis of a link between the observed increase in Chinese real estate prices and the reported rise in shadow banking activities. We expand on these earlier results by using quarterly data on the magnitude of shadow banking from Sun (2019) to examine causal relationships between the housing price index, shadow banking and systemic risk, among others.

The issues related to Chinese shadow banking are similar to those identified in developed economies, with some specific features due to the country's distinct characteristics (Hachem (2018) for a comprehensive review). Securitization and structured investment products increasingly complement the basic functions of asset offloading, regulatory circumvention and maturity mismatch (Ehlers et al. (2018)). When regulated banks act as intermediaries, such as for firm-to-firm entrusted loans, they are not burdened with additional risk. However, when own securities are sold, the final bearer of risk is unclear (Allen et al. (2019)). Indicatively, Tian et al. (2016) find that trust companies were the main source of instability in the Chinese financial system as a whole between 2007 and 2012, and commercial banks suffered the most from its adverse effects. The recent regulatory crackdown seems to have halted the growth rate of the sector, but at the same time increased concerns on profitability, liquidity and non-performing loans (Financial Stability Board (2018)). Importantly, the lack of data and disclosed information, as well as the variety of definitions, make any discussion around shadow banking rather ambiguous. The risk non-performing loans pose was most recently highlighted in August 2021, when the state-owned bad loans manager Huarong reported losses of USD 15.9 billion for 2020, with shareholder equity reduced by 85% and capital buffers far short of regulatory requirements (Bloomberg News (2021)). At the same time Evergrande, the largest property firm in China, reported liabilities of USD 304 billion, which led to a heavy discount of its corporate bonds (The Economist (2021)).

The relationship between shadow banking and the real estate sector is of particular interest. Real estate has become a hub of Chinese domestic interlinkages and the final collateral of multiple financing. It is estimated that about 20 - 25% of assets of pecuniary funds are channeled to the real estate sector[3] (Liao et al. (2016)). Although not as important as that of the financial sector, the risk exposure is significant and the distress of an important construction firm, with a typically high credit rating, can put pressure on the shadow banks which tend to hold short-term bonds from the construction sector. Ding et al. (2017) identify links between real estate and shadow banking. The exposure of banks to the real estate sector is argued to be moderate, but protective barriers are being eroded. Shadow banking in China surged dramatically because the traditional banking system was not structured to accommodate the needs of an increasingly expanding and complex market. Thus, agents in need of credit, such as real estate firms and private borrowers, increasingly use new, non-traditional channels, to obtain debt financing (Elliott et al. (2015)).

2.3. Economic Policy Uncertainty in China

Economic Policy Uncertainty (EPU) indices based on press coverage of economic news have become a popular tool to analyze and forecast stock market risk and returns. Recent findings suggest that these indices can improve volatility forecasting and are positively related to market volatility (Liu and Zhang (2015)). Research focusing on China commonly connects EPU with stock market movements, where EPU tends to be strongly negatively correlated with stock market returns (Yang and Jiang (2016)), or deals with the construction of an appropriate EPU index (Huang and Luk (2020)). However, the literature offers little discus-

[3] A comprehensive summary for the Chinese real estate market can be found in Koss and Shi (2018).

sion on the relationship between news coverage and public sentiment, as captured by such an index, and systemic risk. An exception to this are Sun et al. (2017), who detect varying correlations and both uni- and bi-directional spillovers between systemic risk and policy uncertainty in the US. This is the gap we intend to cover, by using the EPU and Trade Policy Uncertainty index (Baker et al. (2016)) which covers business and economics news published in the Hong-Kong based South China Morning Post. It can serve as an indicator of public sentiment which represents qualitative rather than quantitative shifts (Stolbov et al. (2018)) and international investors are expected to be more attuned to it.

3. Data and methodology

3.1. Indicators of systemic risk in banking

Market-based measures of bank systemic risk attempt to incorporate the views of market participants and can be very useful for assessing whether market participants and regulators agree on the relative systemic importance of individual domestic banks. Within the broad range of Value-at-Risk (VaR) and expected shortfall measures used to assess systemic risk, we select SRISK (Brownlees and Engle (2016), Engle et al. (2014)). Fang et al. (2018) provide evidence that systemic risk measures partially based on book values, such as SRISK, are relatively more accurate than measures relying only on market values, which makes our approach appropriate for the Chinese banking sector. SRISK provides an estimate of how much capital a financial institution would need given a severe distress of the entire stock market. The market-based nature of the measure allows us to examine the effect of a drop in the performance of emerging markets and relate it to the performance of Chinese banks. Since the MSCI EM index provides international investors with a readily available performance benchmark, as well as a representative tool for a wide selection of countries, our adopted methodology captures both the exposure of an investor in emerging markets to the riskiness of the Chinese banking sector as well as the systemic role of those financial institutions.

During stock market declines, the financial system as a whole can be considered as undercapitalized, which makes the undercapitalization of an individual bank more difficult to be absorbed by the market. Therefore, banks which lack capital in such a situation are more likely to require additional funding, bailouts or could even experience bankruptcy. Such funding requirements are closely related to negative externalities (Acharya et al. (2017)), as the VaR of an individual firm affects the VaR of the entire system (Adrian and Brunnermeier (2016)). Thus, SRISK shows not only the capital shortfall of an individual firm, but also the firm's contribution to the total systemic risk of the sector. It captures firm distress conditional on a market crisis and is found to have some predictive power (Brownlees and Engle (2016)). For bank i at time t and for a time interval T, the bank's need for additional capital, or capital shortfall, is defined as

$$CS_{i,t:t+T} = E_t(\theta A_{i,t+T} - W_{i,t+T} | C_{t:t+T}) \tag{1}$$

Where θ is the prudential capital ratio (minimum capital requirements), A the value of assets, W the bank's market capitalization and C the crisis threshold, or the threshold below which the market has fallen enough to be considered in distress. CS, therefore, shows how much capital a bank requires if market distress occurs in order to cover the amount θA required by the regulator given its market valuation. Market capitalization (market value of equity) is used instead of the book value of equity as a proxy of firm value, due to its daily frequency and its dependence on stock price fluctuations, which allows the conditional returns forecast of the test. The total value of assets is proxied by the quasi-value of assets $BA + W - BE$, where BA is the book value of assets and BE the book value of equity. Quasi-market values are used as a reasonable compromise between book and market values of the different variables (Engle et al. (2014)), while the formulation of the test based on assets rather than debt addresses issues of data accuracy, since reported assets are more reliable than reported debt. We set the distress threshold C to -30% for the domestic benchmark and -10% for the international one, on a monthly basis. Finally, the prudential capital ratio is set to 10%[4]. The value of bank debt D is proxied as the difference between the book

[4]The Chinese regulatory framework is stricter than the Basel III provisions, with a minimum capital requirement at 8%, a 2.5% capital conservation buffer, an extra 1% surcharge for Systemically Important Financial Institutions and a $0 - 2.5\%$ counter-cyclical buffer. A reduction of 0.5% was applied in 2018 to

values of debt and equity ($D = BA - BE$), and is considered to remain constant within the observed time intervals. If leverage is defined as $L_{i,t} = A_{i,t}/W_{i,t}$, then $D_{i,t} = (L_{i,t} - 1)W_{i,t}$ and CS becomes $CS_{i,t:t+T} = \theta(L_{i,t} - 1)W_{i,t}(1 - \theta)Et(W_{i,t+T}|C_{t:t+1})$.

The last term can also be expressed as the percentage change of market capitalization of a bank conditional on market distress. Taking $W_{i,t}$ out as a common factor, conditional capital shortfall for bank i can be defined as

$$CS_{i,t:t+T} = W_{i,t}(\theta(L_{i,t} - 1) - (1 - \theta)E_t(1 - LRMES_{i,t:t+T})) \tag{2}$$

where

$$LRMES_{i,t:t+T} = -E_t(R_{i,t:t+T}|R_{M,t:t+T} \leq C_{t:t+T} = -10\%)$$

LRMES is the long-run marginal expected shortfall of bank i for interval T between time t and $t + T$, or the percentage reduction in market capitalization. Default occurs when $LRMES = 1$, where market capitalization is zero. $R_{i,t:t+T}$ and $R_{M,t:t+T}$ are the simple returns over period T (set to one month) for bank i and the market, respectively, based on cumulative log-returns calculated by the forecasting model. Forecasts for LRMES are obtained via GARCH-DCC, following Brownlees and Engle (2016).

The final form of the test is

$$SRISK_{i,t:t+T} = max(0, CS_{i,t:t+T}) \tag{3}$$

or positive capital shortfall. It measures the equity buffer that would be sufficient to overcome a possible financial crisis. SRISK estimates for individual banks can be summed to produce aggregate SRISK for the sample, which in our case is a reliable proxy for the Chinese banking system since the largest and most important financial institutions are included. The fraction of a bank's SRISK over aggregate SRISK allows us to calculate the percentage contribution of each bank to the total.

certain institutions. As compromise across the sample, we adopt a total prudential capital ratio of 10%.

3.2. Interconnectedness measures

In a fully efficient market equity price changes would be random, hence a Granger causality test would not detect any causal relations in returns. However, in the presence of VaR constraints or other market frictions, such as transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on short sales, we may find Granger causality among equity returns. Moreover, this potential forecastability cannot be easily arbitraged away, precisely because of the presence of these frictions. From this perspective, the degree of Granger causality in asset returns can be viewed as a proxy for spillovers among market participants (Danıelsson et al. (2010)). The greater spillover effects imply stronger connections and integration among financial institutions, heightening the severity of systemic events.

In a Granger causality framework one can determine the directional return spillovers in the financial system (composed, in our case, of 17 Chinese banks). Time series j Granger-causes another time series i if the information contained in the past values of i and in the past values of j is more useful in predicting the value of i than the information based only on the past values of i. Formally,

$$(j \to i) = \begin{cases} 1, & \text{if } j \text{ Granger-causes } i \\ 0, & \text{otherwise} \end{cases}$$

and $(j \to j) \equiv 0$. Thus, based on these pairwise Granger causalities, one can construct the Granger-causality network. The network in our case is defined as a set of 17 nodes connected by edges. The size of each node is defined relative to the average market capitalization of a bank over the sample period[5]. The network can be represented as an N_t-dimensional adjacency matrix A_t with the elements α_{ijt} taking values of zero and one, with $\alpha_{ijt} = 1$ if node j Granger-causes node i and $\alpha_{ijt} = 0$ otherwise. Following Billio et al. (2012), the returns are modelled using a GARCH(1,1) process. We focus on the following measures of

[5]More specifically, average market capitalization is calculated over the sample for all banks. The average of each bank is then divided by the mean of all averages. The resulting weights are normalized between 0.2 and 4 for illustration purposes.

connectedness, where α_{ij} denotes a causal connection between banks i and j

The Dynamic Causality Index (DCI) is defined by the following expression:

$$\binom{N_t}{2}^{-1} \sum_{i=1}^{N_t} \sum_{j=1}^{N_t} \alpha_{ijt}$$

and denotes the number of statistically significant Granger-causality relationships among all N(N-1), or 17×16=272 pairs of N=17 financial institutions over time.

The In+Out (IO) and In+Out-Others (IOO) network degrees is defined by:

$$IO_t^i = \sum_{j=1}^{N_t} \alpha_{ijt} + \sum_{i=1}^{N_t} \alpha_{jit}$$

The first part of the right-hand side of the relationship is the IN network degree and measures the number of return series i that significantly (at 5% significance level) Granger-cause institution j, whereas the last part of the right-hand side of the relationship is the OUT network degree and measures the number of return series i that are significantly Granger-caused by institution j. We group our sample into the Big 4 banks (Bank of China, Industrial Commercial Bank of China, China Communications Bank, Agricultural Bank of China) and all other banks. In+Out-Others is the number of return series of other types of firms (Big 4 or all others) that significantly Granger-cause return series j and are significantly Granger-caused by it. Therefore, IOO is essentially a form of IO conditional on the group of a bank and indicates the effect of banks belonging to a particular group. Degree centrality represents the number of connections (degree) in each node. We report the number of connections that are Granger-caused by that bank as well as the number of total connections to the bank, in order to determine whether the bank is affected by more banks than those it affects.

3.3. Data

We collect daily returns and market capitalization data from Thomson Reuters Datastream, for a set of 17 listed Chinese banks and two indices (Table 1). Quarterly data on total assets and shareholder equity is obtained from Compustat and complemented by Thomson Reuters

Eikon data when necessary[6]. The Economic Policy Uncertainty and real residential property prices indices come from the Economic Policy Uncertainty website and the Bank for International Settlements (retrieved from FRED, Federal Reserve Bank of St. Louis) respectively. We report abbreviations, the number of observations (before any interpolation), the date at which data becomes available and the maximum period. The Traditional Shadow Banking and Bank Shadow values are taken from Sun (2019), interpolated to monthly data and converted to billion US dollars by using the end-of-month exchange rate. The real residential property price index is also interpolated to monthly frequency. All amounts are in US dollars and the banks have been selected based on the size and the availability of quarterly data. We assume that international investors would primarily invest in H-shares where available, while domestic investors invest only in A-shares.

[INSERT TABLE 1 HERE]

Our shadow banking proxies, "Bank Shadow" (BSHADOW) and "Traditional Shadow Banking" (TRADSB), are from Sun (2019). The Traditional Shadow Banking measure is defined as credit creation by non-bank financial intermediaries through money transfer, while Bank Shadow is defined as money creation by banks through accounting treatments that generate liabilities, and moves beyond traditional loans. TRADSB is the sum of (i) the claims of financial companies on non-financial companies and households (ii) balance of finance lease contracts (iii) balance of microfinance company loans, and (iv) balance of trust assets, excluding bank trust cooperation. The last category is by far the largest component of the sum. BSHADOW is calculated as M2 plus government deposits (which is negative) plus capital accounts minus the sum of loans, foreign exchange business and corporate bonds holdings.

[6]Missing data points are interpolated from semi-annual observations in a small number of cases.

4. Empirical results

4.1. Systemic risk results

In this section, we estimate SRISK individually for each bank in our sample using both the domestic and emerging markets benchmarks and report aggregate results for each case (Figure 1a). Starting from 01-01-2006, a bank is included in aggregate SRISK when there is enough data to produce an estimate. We present SRISK plots under the domestic index under a -30% distress threshold, which quantitively matches the Chinese stock market declines in 2015-2016, the MSCI EM index under a -10% threshold, which represents observed declines for international indices, and the domestic index under a -10% threshold to compare SRISK under the two benchmarks under the same distress threshold.

All plots in Figure 1a are remarkably similar. While between 2006 and 2011 systemic risk is virtually zero, it starts increasing rapidly in the following years. A brief reduction is observed in 2013 and a large dip in 2015, after which systemic risk remains consistently high and gradually decreases until it surges again in early 2018 to its most recent peak of USD 600 billion under the domestic index and USD 900 billion under the international index. The difference in the estimates is not unexpected, since under a higher threshold (fewer monthly equity market declines that are classified as distress) the times when recapitalization is required are less frequent. Notably, the correlations between the alternative SRISK estimates range between 96.4% and 99.5%, indicating that the results in this and the following sections are robust to the choice of market benchmark. Therefore, for the remainder of section 4.1 we report our findings on the domestic case. The case of the MSCI EM index can be found in Appendix A along with evidence on the robustness of our findings.

[INSERT FIGURE 1 HERE]

The overall observed pattern is very clearly one of increased risk in the financial system, which coincides with our earlier observations on the effect of the Chinese monetary policy on systemic risk. It also agrees with findings that the financial crisis did not affect the Chinese banking system as much as the US and the EU (IMF (2018)). The 2006 - 2011 sample includes 14 out of 17 banks, all of which are globally or systemically important and sufficiently large (apart from Agricultural Bank of China, which underwent IPO in 2010, so the data becomes available in 2011). The Chinese banking system was resilient to the direct financial effects of the 2008-09 global financial crisis, in large part because it was focused on a strongly growing domestic market and had little exposure to overseas wholesale funding markets. The large surge in SRISK during 2011 - 2012 coincides with the end of the 2008 economic stimulus package, which led to a surge in credit volume and asset prices. The 2015 and 2016 Chinese stock market crashes are also associated with the large SRISK increase between May 2015 and August 2016. The next large increase of SRISK in 2018 can be attributed to a combination of factors, such as the crackdown on shadow banking.

Figure 1b separates banks into three categories, given the most inclusive starting points: 1-1-2006 (5 banks), 1-1-2008 (8 banks) and 1-1-2011 (4 banks). The trends are largely similar to those in Figure 1a. Importantly, it appears that limited data availability for earlier dates in our sample does not affect the observed general trend, since SRISK for all groups increases after 2011. Although the majority of banks are already present in the sample in 2008, SRISK in 2006-2010 remains negligible. The increase in SRISK is visible in 2011 for all of the three "inflow" categories of banks, which further supports our insights. This allows us to ignore the starting dates and use the aggregate indicator reported in Figure 1a.

Figure 1c shows the SRISK evolution of the four biggest Chinese banks (Industrial Commercial Bank of China - ICBC, Agricultural Bank of China - ABC, Bank of China - BoC, China Construction Bank - CCB) and all other banks in our sample respectively, in absolute values, and Figure 2 the percentage contributions of each group to aggregate SRISK (Figure 2a) and of each of the four biggest banks (Figure 2b). Since SRISK is effectively zero before 2011, the time scale of Figure 2a is 2011-2018. The individual trends are consistent with the aggregate trend (Figures 1a, 1c), showing that the sector behaves in a surprisingly uniform way. Smaller banks contributed more than the Big Four in 2011-2013 and 2017-2018. Crucially, SRISK remains remarkably similar for both groups throughout the whole period. Smaller banks do not simply mimic the trend of their larger counterparts at a lower overall level but contribute roughly equally to total systemic risk (Figure 2a). This highlights the increased importance of the wider banking sector rather than an improvement of the risk exposure of its flagship institutions. The increasing SRISK contribution of smaller banks becomes more obvious in 2017-2018, where it greatly surpasses that of the biggest banks. The most important contributor of systemic risk after 2014 is ABC, matched by BoC in 2013-2014 (Figure 2b). This is not surprising, given the historically large amount of non-performing loans ABC accumulated (Li et al. (2014)). Between 2011 and 2013, BoC is the prime contributor, while ICBC and CCB move at the same levels and follow the pattern most of the time after 2011.

[INSERT FIGURE 2 HERE]

Finally, Figure 3 shows the percentage contribution of all banks to total SRISK between 2012 and 2018 (December values). Banks with contribution below 3% are added and reported together. The results strengthen the insights gained from the aggregate trends, as they appear to hold for individual banks as well. While the SRISK of ABC dominates every year after 2014, the contribution of the other three biggest banks is by no means negligible, ranging typically at 10-15%. The contribution of smaller banks constantly increases as a total but, individually, they generally contribute 5-9%. A percentage increase implies a shifting of risk across banks but does not prevent a reduction of systemic risk in total, which is in line with our interconnectedness results. Overall, the largest institutions are the main contributors of systemic risk with many smaller banks contributing to a modest degree individually but in a sizable fashion on aggregate. However, all banks appear to be net contributors at some stage, albeit limited. This is a worrying finding when compared to SRISK results for the US banks (Brownlees and Engle (2016)). SRISK in the US between 2005 and 2011 depended almost entirely upon a small number of market leaders, most of which were bailed out or went bankrupt, such as Fannie Mae, Freddie Mac and Lehman Brothers. Notably, the SRISK estimate for those three institutions ranged between 8 and 9% of total SRISK, only slightly higher than the estimates for the non-Big 4 Chinese banks. This indicates two things for the Chinese banking system. Firstly, an institution may still cause a systemic event even if its SRISK is relatively low. Secondly, a larger number of banks is capable of causing a systemic event.

[INSERT FIGURE 3 HERE]

Our results indicate that systemic risk is widely spread in the Chinese financial system, leaving no bank unaffected. The most important banks are also likely to be the most undercapitalized in the case of a market distress. The part of systemic risk allocated to the 13 smaller banks of our sample is roughly equal to that of the four biggest institutions, but individual smaller banks contributed consistently up to 10% of aggregate SRISK. This matches empirical and industry observations that mid-tier and regional banks have become riskier, as demonstrated by a series of bailouts in this market segment. The rapid increase of SRISK after 2012 can be attributed to excessive risk taking, an increasing amount of non-performing loans, high interest rate spreads and significant expansion in credit volume, primarily from cross-regional banks (Zhu et al. (2019), Zhang et al. (2018)). Using a sample of Chinese commercial banks between 2006 and 2010, Qian et al. (2015) suggest that government ownership has no effect on prudential bank behavior, while having government officials appointed as board directors has a negative effect. In addition, high bank capital requirements are likely to increase risk-taking after a certain level (Jiang et al. (2019)).

A small value of SRISK may well represent a loss of capital enough to put the bank under distress, which can cause contagion. Our findings are in line with industry and academic observations on the riskiness and interconnectedness in the Chinese financial system. They are also consistent with the literature discussed earlier on the paired relationships between the real estate market, banks and the shadow banking sector. The increase in systemic risk also matches the observed trends in bank consolidation and a general reduction in the number of banks in China.

4.1.1. The role of government guarantees

Our results so far have not considered the potential effect of changes in the Chinese banking regulation and government guarantees, which could disproportionately affect banks of different size. For example, one could argue that changes in SRISK can be partially attributed to changes in the perceived likelihood of a bailout of larger and smaller banks. A notable example of key regulatory developments in China is the Deposit Insurance Regulation, which was promulgated by the State Council on 17 February 2015 and came into force on 1 May 2015. Importantly, there was no explicit deposit insurance in China before that date. Relevant to our paper, Yamori and Sun (2019) argue that the introduction of deposit insurance in China allowed a redistribution of wealth from small to large banks in the short time frame considered in the paper. As this observation is consistent with our results on the evolution of SRISK, we address this issue further in Appendix C. We estimate a Markov switching model to examine if there are any regime changes in systemic risk at the times when new legislation is introduced, most importantly the introduction of government guarantees.

The results in Appendix C are consistent with the argument that new government regulation and guarantees may affect SRISK. The transitions between the high and the low risk states for the large and small banks tend to happen simultaneously (Figure C.10). The state transitions are consistent with some changes in government guarantees, such as the increase in SRISK in the period after the introduction of deposit insurance in 2015. However, the increase in SRISK also coincides with the Chinese stock market turbulence between June 2015 and February 2016. Therefore, we cannot rule out the effect of changes in government regulation on the SRISK of banks but there is little evidence supporting the heterogeneous effect of changes in regulation on small and large banks. A more comprehensive data set and empirical framework are required for more robust empirical results.

4.2. SRISK, real estate prices, shadow banking and policy uncertainty

Our results on the systemic risk of Chinese banks indicate its strong upward trend over time and significant changes in the distribution of individual contributions of the banks. The literature discussed earlier also suggests that the growing shadow banking sector, the soaring housing prices, and an increase in economic policy uncertainty are likely to be positively associated with systemic risk. We conduct estimations and report results for SRISK under both the MSCI EM benchmark and the domestic market index. Our findings are qualitatively the same, so for brevity we report the results for the international case in this section and for the domestic case in Appendix A.

Figures 4a and 4b depict the real residential property prices (housing price index) for China together with the aggregate SRISK plot and the Hong Kong-based EPU index, along with aggregate SRISK together with the traditional shadow banking and bank shadow indicators. The housing price index peaked in 2018 and has been growing rapidly after 2015, in a manner similar to SRISK. Moreover, the joint plot reveals that after 2011, when SRISK first increased, the index follows the evolution of systemic risk while prior to that they appear to be unrelated. EPU moves closely with SRISK after 2015, a period which coincides with two stock market crashes in China. Similar trends are observed between the SRISK and shadow banking indicators.

[INSERT FIGURE 4 HERE]

We hypothesize that all the indicators we discuss contribute to the rise in systemic risk between January 2011 and September 2018. We examine cointegration and causality between systemic risk (SRISK), the Chinese real residential property price index (PROPP) (or "housing price(s)"), the Economic Policy Uncertainty index, traditional shadow banking (TRADSB) and bank shadow (BSHADOW). This allows us to shed further light onto the interplay between the real estate market and the shadow banking sector, an issue that, with the exception of Lai and Van Order (2019) has been studied indirectly only. Although not central to our research questions, Appendix B expands on the relationship between SRISK and macroeconomic variables, namely DGP, Total Industrial Production and the Exports-to-Imports ratio.

4.2.1. Cointegration and causality relationships

A series of Augmented Dickey-Fuller tests (Table 2) shows that all series are I(1) at levels and become stationary after taking first differences. A Johansen cointegration test, which is more suitable for small samples, is conducted for all pairs and groups of the time series at the variable levels. Following Turner (2009), we use the MacKinnon et al. (1999) critical values because they are the most robust if there is a mismatch between the critical values used and the specification of the vector error correction model (VECM). The starting point is January 2011 because that is when systemic risk becomes effectively non-zero, and also all banks are present in our sample at that time. We apply the test on the log transformation of the series, with amounts in billion USD where applicable.

[INSERT TABLE 2 HERE]

The results (Table 3) show the existence of cointegration between all pairs, which implies co-movement between each couple of variables and is in line with Figures 4a and 4b. When the variables are grouped, the existence of at least one cointegrating relationship is also shown. However, a series of unreported VAR estimations and Granger causality tests using the first-differenced series showed no causality. Therefore, we conclude that there always is at least one cointegrating relationship at the levels of the time series and in order to infer causality we estimate the corresponding VECM models with one fewer lag than the VAR model, as defined by the Akaike, Schwarz and Bayesian Information Criteria. Similar to the Johansen tests, we estimate VECMs in pairs and groups of time series and examine long- and short-term causality relations. The results and specifications of each model can be found in Table 4.

[INSERT TABLE 3 HERE]

Panel A in Table 4 reports the VECM results for the pairs of time series that are central to the paper. We are particularly interested in whether SRISK is affected by other indicators in the long- and short-run, the relationship between PROPP and the two shadow banking proxies, and whether bi-directional causality is present in the data. When SRISK is the dependent variable, the error correction term (ECT) is negative and statistically significant for all four pairs at either 1% or 5% significance level. This indicates a long-run causal relationship flowing from policy uncertainty, property prices and the shadow banking sector towards systemic risk. Moreover, the lagged terms of PROPP and EPU are statistically significant at 5% and 10% significance levels, which demonstrates the casual relationship between variables in the short-run. This verifies our intuition that the reasons behind the recent and persistent increase in systemic risk can be traced to the increase in housing prices as well as the increased public concerns about economic policy, captured by news coverage. This co-movement is robust and stable, as demonstrated by the negative signs of the error correction terms which technically signify convergence to the long-run equilibrium of the cointegration relationship. Importantly, the observed causal relationships are uni-directional for the housing prices and bank shadow indicators. When the pairs are reversed and SRISK becomes the independent variable in the VECM, the error correction terms are not statistically significant.

[INSERT TABLE 4 HERE]

On the contrary, causality in the EPU/ SRISK and TRADSB/ SRISK pairs is bi-directional and only observed in the long-run, since only the ECTs are statistically significant. It must be noted that the ECT for TRADSB/ SRISK is positive, which signifies an unstable cointegration relationship. This result reappears when the VECM contains 3 and 4 variables and is robust across different model and lag specifications, which supports the importance of indicator construction for shadow banking. Our findings signify the need to reexamine the relationship between shadow banking and systemic risk in the future using a variety of measures. Finally, the PROPP/ TRADSB and PROPP/ BSHADOW pairs show that there is a long-run causal relationship flowing from both proxies of systemic risk to the property price index. However, there is no short-term causality since only the ECTs are statistically significant but the lagged terms are not. The results for the reversed pairs support uni-directional causality. It must be stressed that, with the exception of the positive error correction term for the TRADSB/ SRISK pair, all other results have a negative sign which shows a stable cointegration relationship and convergence to the long-run equilibrium.

Table 4, Panel B examines the simultaneous interplay between SRISK, PROPP and EPU. There is stable long- as well as short-run causality from economic policy uncertainty and property prices when they are jointly included in the model, as shown by the statistically significant and negative ECT and lagged terms. This strengthens our results for the pairs. There is no causality when PROPP becomes the dependent variable, but it is observed in the case of EPU. This further underlines that property prices and policy uncertainty jointly contribute to systemic risk and there is some evidence of systemic risk and property prices affecting policy uncertainty. Property prices appear to affect but not be affected by SRISK and EPU.

Finally, we conduct two 4-variable VECMs (Panels C and B), one for each shadow banking proxy, with all other variables present. In the SRISK/ EPU/ PROPP/ TRADSB group, the ECT is still negative and statistically significant, but only EPU shows short-term causality. The only other case where the ECT is statistically significant is when TRADSB is the dependent variable, but the sign is positive. SRISK also appears to affect shadow banking in the short-run. When the bank shadow indicator is used instead of traditional shadow banking, the results are largely similar with some additional features. First, long-run causality is observed when EPU is the dependent variable. Second, when BSHADOW is the dependent variable, both SRISK and EPU exhibit short-run causality. No causality is detected in relation to property prices.

We therefore demonstrate an intricate network of interactions, where the influence of housing prices, shadow banking and economic policy uncertainty on systemic risk is persistent across different cases, both in the long- and the short-run. This shows that there is a robust causal relationship from all four proxies to SRISK, which validates our earlier intuition that an increase in systemic risk can be attributed to an increase in shadow banking activities, a rise in residential property prices and increased economic policy uncertainty. The results also suggest that systemic risk affects shadow banking when policy uncertainty and property prices are considered, but not in isolation. It is important to notice that the causal relationship between PROPP and SRISK shows that an increase in property prices leads to an increase in systemic risk, not the other way around. Economic policy uncertainty frequently appears to act both as a causal factor and the recipient of causal effects when all factors are present. Finally, both shadow banking proxies influence property prices when examined in isolation, but this relationship is not statistically significant in the short-run in the joint estimation.

Our results show a striking similarity with the well-documented pre-crisis patterns in many countries. The relationship between the US housing bubble, securitization of the US real estate loans and general accumulation of risk would typically be associated with a surge in asset prices prior to the outbreak of the financial crisis has been well documented. Our results indicate a similar story for the Chinese financial and real estate sectors. As discussed earlier, increased debt in both households and real estate firms leads to an increased need for financial resources and liquidity in order to cover the increased demand for housing and real estate. The Chinese shadow banking sector acts as a provider of such liquidity through maturity transformation of corporate debt. The findings also suggest a joint increase in systemic risk and economic policy uncertainty, as reflected by media coverage. The increase in uncertainty is quite pronounced after 2011, which covers the post-crisis asset bubble, the 2015-2016 period of market turbulence, the expansion of the shadow banking sector and the ongoing regulatory reforms in the financial sector.

4.2.2. Systemic risk and macroeconomic factors

A full exploration of the relationship between systemic risk and the macroeconomy (GDP growth, unemployment, public and private investment, industrial growth, etc.) is beyond the aims of the paper and it is not our intention to construct an equilibrium model that accounts for systemic risk and its determinants. Nevertheless, we acknowledge that the factors we use are closely interconnected with the macroeconomic developments in the Chinese economy. In fact, according to Baker et al. (2016), innovations in policy uncertainty foreshadow declines in investment, output, and employment, and Brownlees and Engle (2016) find that unemployment and industrial production are related to lagged observations of systemic risk in the USA. Although a lot of macro indicators for China are not available at the required frequency, Appendix B expands on the relationship between SRISK and three macroeconomic indices taken from FRED; GDP, Total Industrial Production and the Exports-to-Imports ratio. Our VECM results, presented in Table B.8, Appendix B, show that there is long-term causality from all three macro variables to SRISK, but no short-term causality. Our findings on the short- and long-run casual relationships of SRISK with the factors selected appear to be consistent with what we hypothesized based on conventional economics and finance theory, but more research in this area is warranted.

5. Interconnectedness

In the case of a systemic event, the decline in the equity price of a distressed bank is likely to cause spillover effects to other institutions. Therefore, it would be beneficial to examine whether any relationships between the equity returns of the financial institutions in our sample match our earlier findings. We follow the methodology of Billio et al. (2012) and analyze Granger-causality networks between banks and re-examine whether the biggest institutions dominate the sector or, as our findings on SRISK showed, smaller banks appear to play an important role (Figure 5). As Billio et al. (2012) note, VaR-based and (Granger) interconnectedness measures are complementary, not mutually exclusive, since, unlike VaR, interconnectedness measures rely on predictive rather than contemporaneous relationships. Correlations of banks' equity returns tend to increase during and after a systemic event, not before. Therefore, by conditioning on extreme losses, conditional shortfall measures are estimated on data that reflect unusually high correlations.

[INSERT FIGURE 5 HERE]

This, in turn, implies that during non-crisis periods the correlation of equity returns is unlikely to be useful as an indicator of an increase in systemic risk. Moreover, SRISK is unable to capture the linkages between banks and spillover effects by construction, since it focuses on a single bank, while Granger causality captures those very relationships in a forward-looking manner. Figure 5 reports the network over the sample period between January 2011 and September 2018. The period is selected based on our SRISK results. Degree centrality and the ordering of the banks according to the number of connections can be found in Table 5.

Table 5 shows that none of the four biggest banks ranks at the top as either a bank that Granger-causes a high number of connections or with a very high overall number of connections. ABC is at the third and sixth place, respectively, while all others are at the middle of the list. As the size of the nodes in Figure 5 indicates, the banks which Granger-cause the most connections are medium-sized banks. China Merchants Bank and China CITIC Bank occupy the first two places with 13 and 12 connections each, with ABC and Everbright in the third place with 11 connections. The other Big 4 rank even lower, since Ping An Bank, Chongqing Bank and Bank of Nanjing share the fifth place with 10 connections followed by Bank of China at the eight place with 11 Granger-caused connections. The 5 banks above ABC in the number of total connections also rank at the top positions in the number of causal relationships they cause.

[INSERT TABLE 5 HERE]

The Big 4 bank that ranks highest, Agricultural Bank of China, is at the sixth place together with Industrial Bank, Bank of Communications and China CITIC Bank, with 12 connections. Bank of Nanjing and Everbright are at the first place with 16 connections, followed by Ping An (15 connections) in the third, Chongqing (14) in the fourth and China Merchants Bank (13) in the fifth position. This indicates that smaller institutions have also become more interconnected, and a severe drop in their returns is likely to have a wider than believed impact in the banking sector. The SRISK results suggest that those banks also bear an increasing portion of systemic risk. Based on the causal relationships we detect, we conclude that a distress in a firm with many causal connections (typically a smaller institution in our sample) brought by a systemic event is likely to bring a fall in the share price of that bank, which will affect a significant number of institutions to a lesser or greater extent. The direction of those spillover effects is inferred by the Granger causality detected, and we emphasise that the transition mechanism we are able to detect passes through returns and the stock market.

The increase in interconnectedness over time during the sample period is depicted in Figures 6a and 6b. Figure 6a reports the number of In + Out (IO) and In + Out - Other (IOO) connections and Figure 6b reports the Dynamic Causality Index. In both figures, a clear increase in the number and intensity of the causal relationships over time between the institutions in our sample can be seen. The difference between IO and IOO becomes most pronounced after mid-2016, where it solidifies. This is in line with our results on systemic risk and the relatively reduced role of the Big 4 in recent years. The smaller banks in our sample have gradually become both the most connected and the most influential. Notably, they are not the recipients but the facilitators of causality both among themselves and with the four biggest banks. Our findings also agree with Wang et al. (2018), who also find some small firms to be systemically important due to their high level of in- or out-connectedness. Figure 5 shows that mid-ranking banks are also the most central in the financial system. This matches our earlier observations and demonstrates how the smaller banks have begun to play a more important role in the Chinese financial system.

[INSTERT FIGURE 6 HERE]

5.1. The relationship between the SRISK and interconnectedness measures

Individual and VaR-based measures such as SRISK are complementary, both technically and conceptually. Conceptually, SRISK measures potential market value losses over a monthly period conditional on a market decline for a single institution, without considering any positive or negative spillovers to and from other firms in the sector. On the contrary, interconnectedness uses the information captured in equity returns to examine potential spillover channels between firms, without considering a specific systemic event or a firm's individual riskiness. The obtained network of banks, unlike SRISK, does not depend on a market shock and merely identifies how closely connected bank equity returns are. In our view, a discussion on systemic risk posed by an individual bank clearly benefits from a complementary discussion on the inter-bank channels that may cause that risk to spread from institution to institution. Technically, the most important monthly SRISK inputs are daily bank equity returns and market capitalization. Equity returns are also used to form Granger causality networks between banks, so Granger causality within the network effectively captures a transmission channel for systemic risk across banks.

To illustrate that interconnectedness networks can also depict transmission channels of systemic risk, we select Everbright, a smaller yet influential bank, and examine Granger causality between the first differences of the monthly (logged) SRISK series between it and all other banks in our sample, using the lags determined by standard information criteria. We opt for VAR at first differences rather than VECM at levels because it creates a rate of change for SRISK. This is the same concept as Granger causality in returns (rather than prices) in the main paper, which allows us to show whether a causal relationship between the systemic risks of two banks is detected (Table 6).

[INSERT TABLE 6 HERE]

There is a significant number of causal relationships from Everbright to other firms. This includes three large banks (ABC, ICBC, BoC) and 6 smaller institutions. Shanghai Pudong and Minsheng Bank are the only banks Granger-causing Everbright, while there is bidirectional causality with Industial Bank. These findings are largely similar to our main results, where Everbright Granger-causes 10 institutions and is Granger-caused by 13. The main loss of nuance is the lack of bidirectional causality, which is due to the lower, monthly, data frequency compared to the daily frequency of Table 5. We thus show that bank equity returns can be a transmission channel for systemic risk because they are a vital component of both SRISK and interconnectedness networks. Since book values are measured quarterly, the greater part of month-to-month variation comes from market values of assets (market capitalization) which change daily. This bridges the conceptual and technical gap between the two approaches.

6. Conclusion

Our paper utilizes the SRISK measure of Brownlees and Engle (2016) and the network measures of Billio et al. (2012) in order to assess the stability of the Chinese banking system, in light of its massive post-crisis expansion. It also examines causality relationships among banks and between SRISK, the Chinese Economic Policy Uncertainty index, the Chinese real residential property price index and two shadow banking proxies.

Our first key finding is that Chinese banks that are not among the top largest banks are becoming increasingly significant as net contributors of systemic risk in the Chinese banking sector. The risk those institutions pose has become more significant in recent years, in terms of both individual capital requirements in the presence of a market shock, as well as in terms of network spillover effects among banks. Over the last decade, the contribution of the four biggest banks to the increase of systemic risk has been declining relative to that of their smaller counterparts, which have become more influential.

Our second key finding is that the increase in systemic risk can be attributed to all the factors considered. The expansion of the shadow banking sector, the increase in housing prices and the rise in economic policy uncertainty contribute to the observed surge in systemic risk in recent years. This finding is robust and appears both when the indicators are paired and when examined in groups in the long-run. When shadow banking is excluded, there is causality from EPU and property prices to systemic risk in both the short- and the long-run. In addition, there is a causal relationship from shadow banking towards the property price index, which is a novel result. Finally, we report some evidence of bi-directional causality from SRISK to shadow banking and EPU. The results are clear on the causes of the increase in systemic risk and illustrate further interactions between the variables. The common relationship between fragility in the financial system and increasing real estate prices can, to some extent, be attributed to the expansion of shadow banking, which acts both as intermediary between the real estate and the banking sectors and a way for banks to offload risky assets and engage in otherwise regulated activities.

Thus, domestic and international investors should be concerned about smaller Chinese banks and their effect in financial stability. Our main policy suggestion is that further regulatory changes need to focus not just on the biggest institutions, traditionally deemed as more systemically important, but also on smaller banks. Their increased exposure and connectedness may trigger a chain reaction with wider repercussions significantly larger than their individual size. As an indicator of the amount of additional funding that may be required in the case of distress, the maximum value of aggregate SRISK (\$864 billion), is 6.32% of the Chinese nominal gross domestic product in 2018 (\$13.68 trillion). Although significant state ownership precludes a bankruptcy similar to that of Lehman Brothers, our findings suggest that both the number of potentially distressed banks and their capital requirements may be higher than currently assumed.

References

Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M., 2017. Measuring systemic risk. The Review of Financial Studies 30, 2–47.

Adrian, T., Brunnermeier, M.K., 2016. CoVaR. The American Economic Review 106, 1705.

Allen, F., Qian, Y., Tu, G., Yu, F., 2019. Entrusted loans: A close look at China's shadow banking system. Journal of Financial Economics 133, 18–41.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. The quarterly journal of economics 131, 1593–1636.

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of financial economics 104, 535–559.

Bloomberg News, 2018. China Needs Bailout, Capital Plans for Crisis Event: PBOC's Ma (7 December). Bloomberg.

Bloomberg News, 2021. Huarong Posts \$15.9 Billion Loss as Leverage Hit 1,333 Times (29 August). Bloomberg.

Brownlees, C., Engle, R.F., 2016. SRISK: A conditional capital shortfall measure of systemic risk. The Review of Financial Studies 30, 48–79.

Chen, M.S., Kang, J.S., 2018. Credit booms - is China different? IMF Working Paper, WP/18/2 .

Chen, Q.a., Du, F., 2016. Financial innovation, systematic risk and commercial banks' stability in China: theory and evidence. Applied Economics 48, 3887–3898.

Danıelsson, J., Shin, H., Zigrand, J., 2010. Risk appetite and endogenous risk. Available at http://www.lse.ac.uk/fmg/assets/documents/papers/discussion-papers/DP647.pdf .

Ding, D., Huang, X., Jin, T., Lam, W.R., 2017. Assessing China's residential real estate market. IMF Working Paper, 17/248 .

Ehlers, T., Kong, S., Zhu, F., 2018. Mapping shadow banking in China: structure and dynamics. BIS Working Paper .

Elliott, D., Kroeber, A., Qiao, Y., 2015. Shadow banking in China: A primer. Economic Studies at Brookings 3, 1–7.

Engle, R., Jondeau, E., Rockinger, M., 2014. Systemic risk in Europe. Review of Finance 19, 145–190.

Fang, L., Sun, B., Li, H., Yu, H., 2018. Systemic risk network of Chinese financial institutions. Emerging Markets Review 35, 190–206.

Fang, L., Xiao, B., Yu, H., You, Q., 2018. A stable systemic risk ranking in China's banking sector: Based on principal component analysis. Physica A: Statistical Mechanics and its Applications 492, 1997–2009.

Financial Stability Board, 2018. Global Shadow Banking Monitoring Report 2017. Bloomberg News.

Gang, J., Qian, Z., 2015. China's monetary policy and systemic risk. Emerging Markets Finance and Trade 51, 701–713.

Hachem, K., 2018. Shadow banking in China. Annual Review of Financial Economics 10, 287–308.

Huang, Y., Luk, P., 2020. Measuring economic policy uncertainty in China. China Economic Review 59, 101367.

IMF, 2018. Global Financial Stability Report April 2018: A Bumpy Road Ahead. International Monetary Fund.

Jiang, H., Zhang, J., Sun, C., 2019. How does capital buffer affect bank risk-taking? new evidence from China using quantile regression. China Economic Review In press, available at https://doi.org/10.1016/j.chieco.2019.04.008.

Koss, R., Shi, X., 2018. Stabilizing China's housing market. IMF Working Paper, 18/89 .

Lai, R.N., Van Order, R.A., 2019. Shadow banking and the property market in China. International Real Estate Review Forthcoming, available at http://dx.doi.org/10.2139/ssrn.2788012.

Lardy, N.R., Subramanian, A., 2011. Sustaining China's economic growth after the global financial crisis. Peterson Institute.

Li, J., Hsu, S., Qin, Y., 2014. Shadow banking in China: institutional risks. China Economic Review 31, 119–129.

Liao, M., Sun, T., Zhang, J., 2016. China's financial interlinkages and implications for inter-agency coordination. IMF Working Paper, 16/181 .

Liu, L., Zhang, T., 2015. Economic policy uncertainty and stock market volatility. Finance Research Letters 15, 99–105.

MacKinnon, J.G., Haug, A.A., Michelis, L., 1999. Numerical distribution functions of likelihood ratio tests for cointegration. Journal of applied Econometrics 14, 563–577.

OECD, 2018. Business and Finance Outlook 2018. OECD.

People's Bank of China, 2014. China Financial Stability Report 2014. available at http://www.centerforfinancialstability.org/fsr/chn_fsr_201407.pdf.

Qian, X., Zhang, G., Liu, H., 2015. Officials on boards and the prudential behavior of banks: Evidence from China's City commercial banks. China Economic Review 32, 84–96.

Stolbov, M., Karminsky, A., Shchepeleva, M., 2018. Does economic policy uncertainty lead systemic risk? A comparative analysis of selected European countries. Comparative Economic Studies 60, 332–360.

Sun, G., 2019. China's shadow banking: bank's shadow and traditional shadow banking. Bank for International Settlements Working Paper No 822 .

Sun, L., 2020. Financial networks and systemic risk in China's banking system. Finance Research Letters 34, 101236.

Sun, X., Yao, X., Wang, J., 2017. Dynamic interaction between economic policy uncertainty and financial stress: A multi-scale correlation framework. Finance Research Letters 21, 214–221.

The Economist, 2021. China's toxic twins. The Economist 440, 9–10.

Tian, G., Li, J., Xue, Y., Hsu, S., 2016. Systemic risk in the Chinese shadow banking system: A sector-level perspective. Emerging Markets Finance and Trade 52, 475–486.

Turner, P., 2009. Testing for cointegration using the Johansen approach: are we using the correct critical values? Journal of Applied Econometrics 24, 825–831.

Wang, G.J., Jiang, Z.Q., Lin, M., Xie, C., Stanley, H.E., 2018. Interconnectedness and systemic risk of China's financial institutions. Emerging Markets Review 35, 1–18.

Williams, G., 2018. The Evolution of China's Banking System, 1993–2017. Routledge.

Xu, Q., Chen, L., Jiang, C., Yuan, J., 2018. Measuring systemic risk of the banking industry in China: A DCC-MIDAS-t approach. Pacific-Basin Finance Journal 51, 13–31.

Yamori, N., Sun, J., 2019. How did the introduction of deposit insurance affect chinese banks? an investigation of its wealth effects. Emerging Markets Finance and Trade 55, 2022–2038.

Yang, M., Jiang, Z.Q., 2016. The dynamic correlation between policy uncertainty and stock market returns in China. Physica A: Statistical Mechanics and Its Applications 461, 92–100.

Zhang, D., Cai, J., Dickinson, D.G., Kutan, A.M., 2016. Non-performing loans, moral hazard and regulation of the Chinese commercial banking system. Journal of Banking & finance 63, 48–60.

Zhang, L., Hsu, S., Xu, Z., Cheng, E., 2018. Responding to financial crisis: Bank credit expansion with Chinese characteristics. China Economic Review In press, available at https://doi.org/10.1016/j.chieco.2018.09.014.

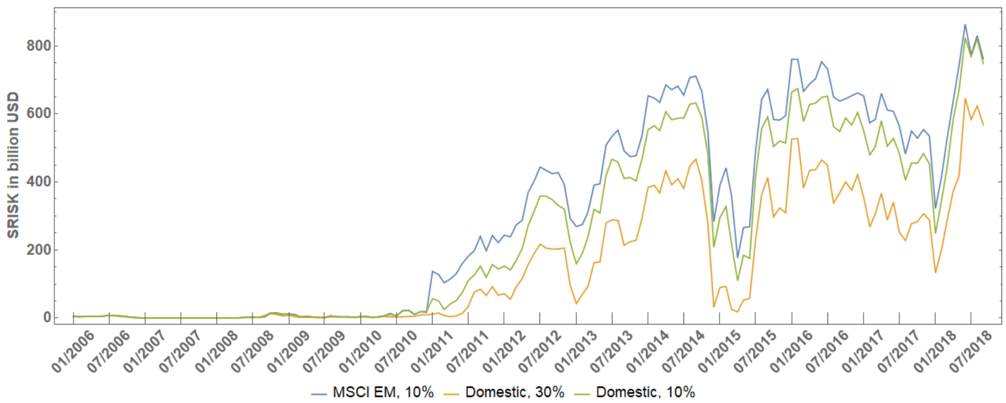
Zhu, N., Wu, Y., Wang, B., Yu, Z., 2019. Risk preference and efficiency in Chinese banking. China Economic Review 53, 324–341.

Variable	Obs.	μ	σ	Min	Max	Frequency
MSCI-EM log-returns (%)	3,324	0.012	1.265	-9.994	10.073	Daily
DS China index log-returns (%)	3,269	0.039	1.877	-13.507	15.723	Daily
Bank log-returns (%)	50,407	0.035	2.199	-23.563	22.596	Daily
Bank Market Capitalization	50,407	63.887	74.268	1.469	485.023	Daily
Bank Total Assets	747	772.739	927.905	8.792	4,223.731	Quarterly
Bank Shareholders Equity	747	52.580	68.565	0.657	346.189	Quarterly
EPU Index	153	188.070	130.800	26.140	694.850	Monthly*
Bank Shadow	52	2,749.589	2,452.734	487.665	7724.668	Quarterly*
Traditional Shadow Banking	32	2,454.598	1,259.021	461.333	4685.663	Quarterly**
Real Residential Property Price Index	52	97.330	4.620	88.530	109.450	Quarterly*

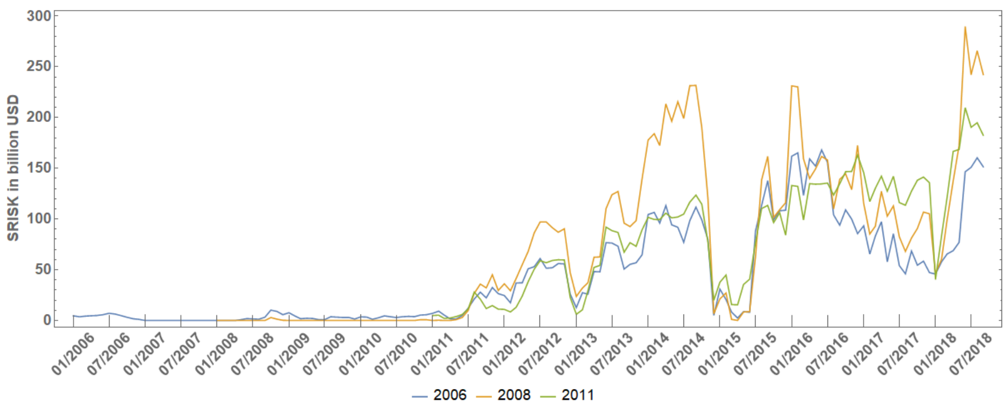
Bank	Abbreviation	Period	Bank	Abbreviation	Data Period
Agricultural Bank of China	ABC	1/11 - 9/18	China Everbright Bank	EVER	1/11 - 9/18
Bank of China	BOC	1/07 - 9/18	Bank of Nanjing	NANJ	1/08 - 9/18
China Construction Bank	CCB	1/06 - 9/18	Bank of Communications	COM	1/06 - 9/18
China CITIC Bank	CITIC	1/08 - 9/18	Chongqing Bank	CHON	1/11 - 9/18
China Merchants Bank	MERCH	1/07 - 9/18	Huaxia Bank	HUA	1/06 - 9/18
Bank of Ningbo	NING	1/08 - 9/18	Industrial Bank	IND	1/08 - 9/18
Industrial Commercial Bank of China	ICBC	1/07 - 9/18	Shanghai Pudong Bank	SHAN	1/06 - 9/18
Minsheng Bank	MINS	1/10 - 9/18	Ping An Bank	PING	1/06 - 9/18
Bank of Beijing	BEI	1/08 - 9/18			

TABLE 1
Sample summary statistics

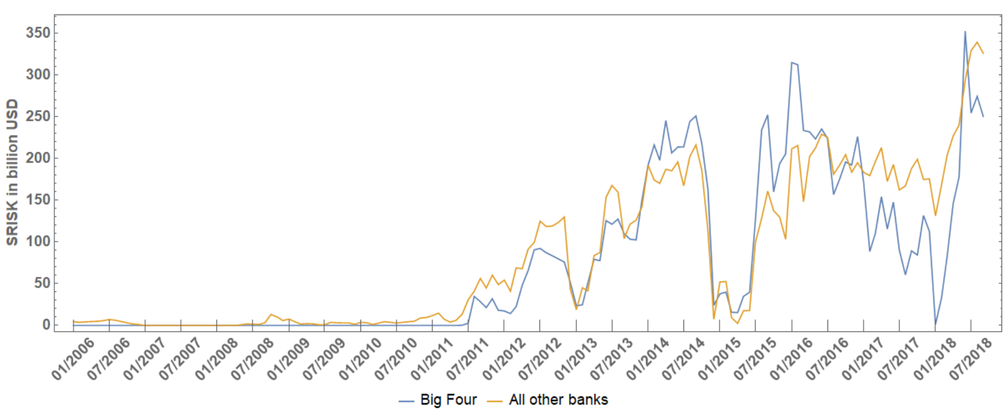
Note: Non-index values in billion US dollars. Periods: January 2006 - September 2018 (*), January 2011 - September 2018 (**). Observations before interpolation where applicable.



(a) Aggregate SRISK (all banks) for the Datastream domestic index under 10% and 30% distress thresholds and the MSCI EM index

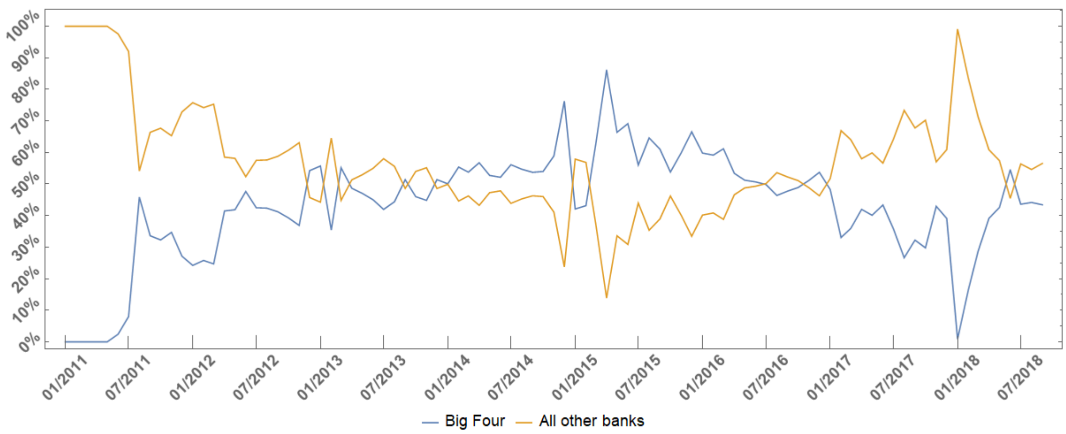


(b) Aggregate SRISK per entry year. 2006: CCB, BoComms, Huaxia, Ping An, Shanghai Pudong. 2008: BoC, ICBC, Merchants, CITIC, Beijing, Nanjing, Ningbo, Industrial. 2011: Minsheng, ABC, Everbright, Chongqing

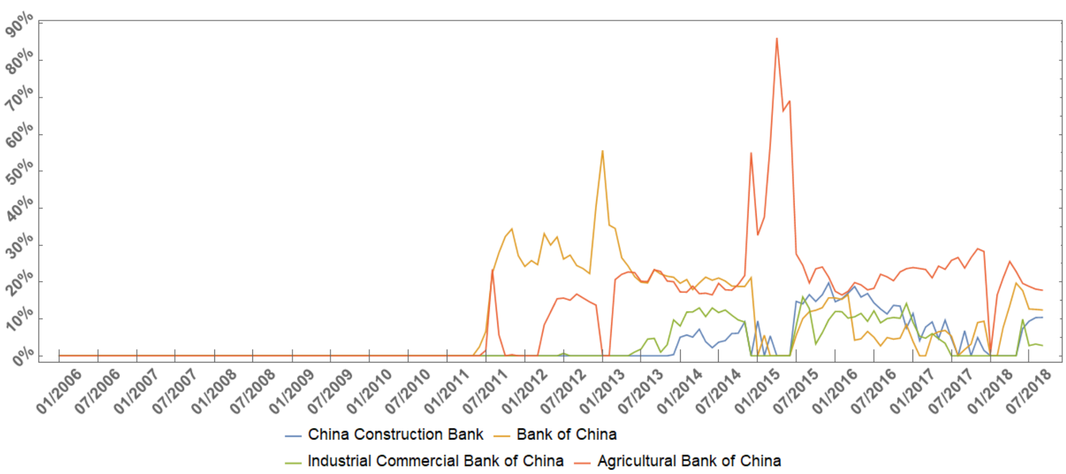


(c) Total SRISK of the Big Four (CCB, BoC, ICBC, ABC) and all other banks

FIGURE 1



(a) Group contributions (%) to total SRISK of the Big Four and all other banks



(b) Contribution (%) of each of the Big Four banks to total SRISK

FIGURE 2

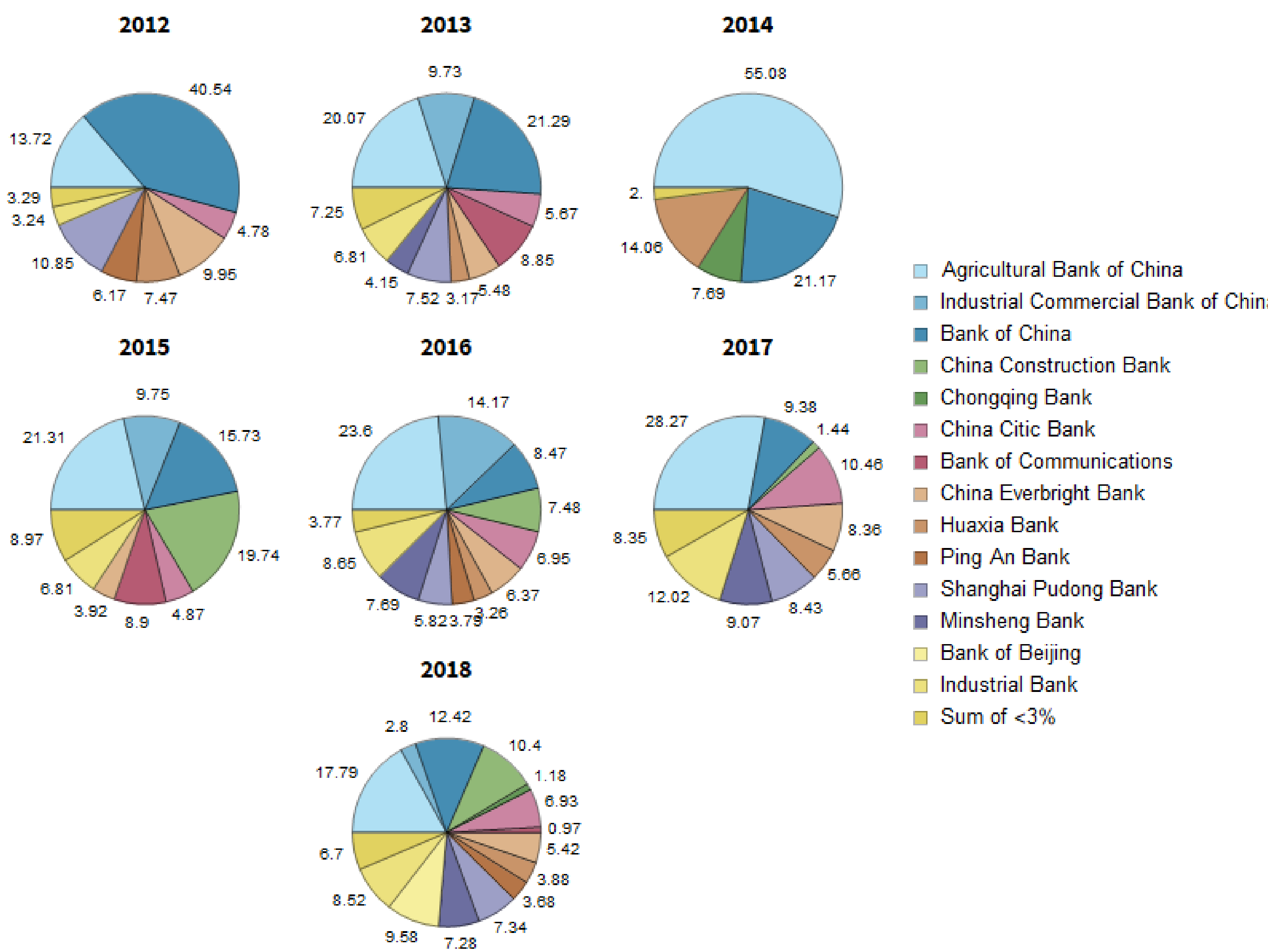
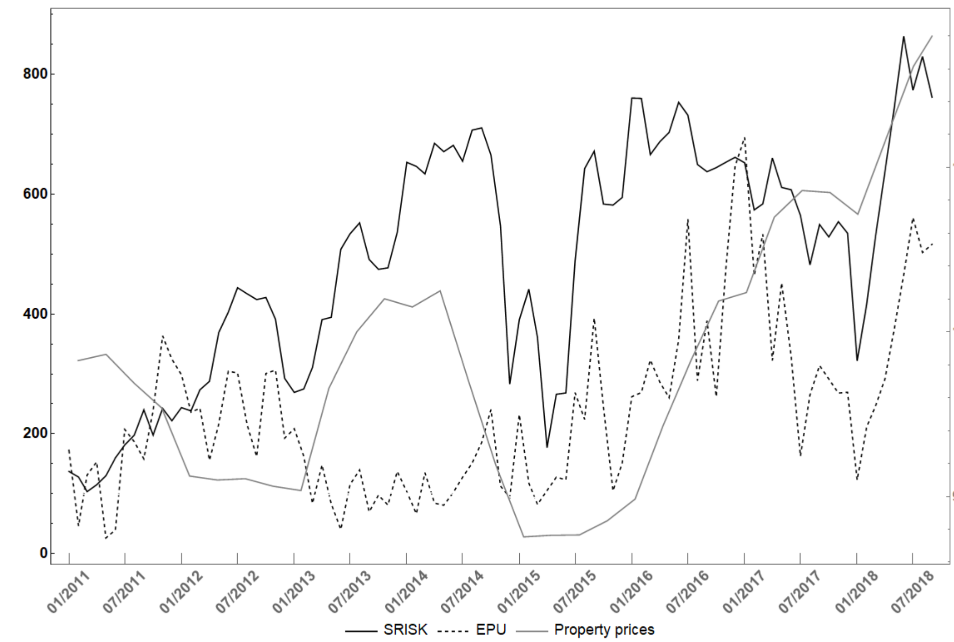
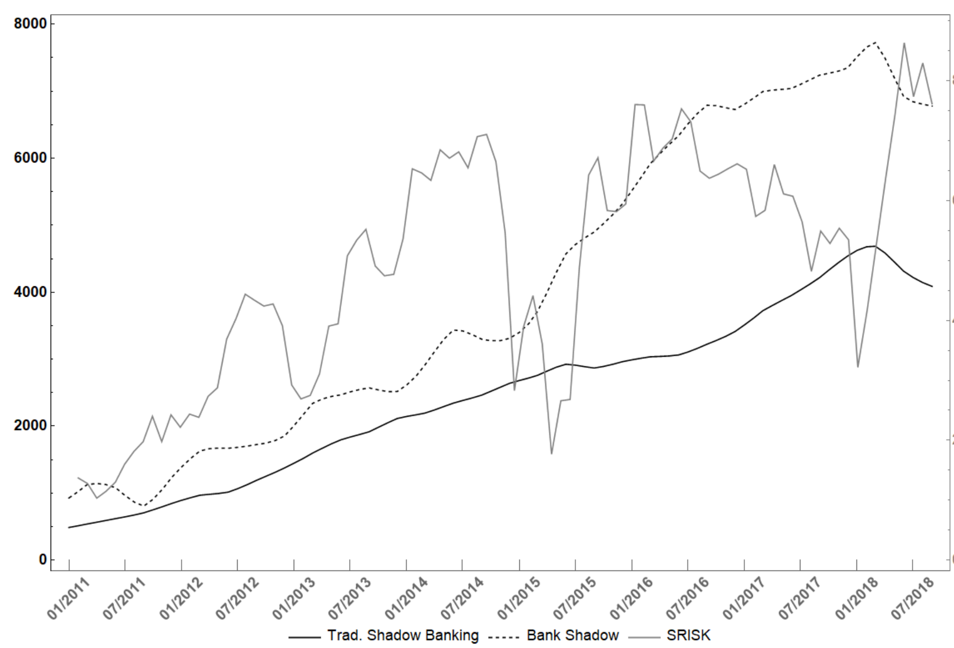


FIGURE 3
Percentage contribution of each bank in aggregate SRISK per year, December 2012 - 2018



(a) Original data of SRISK (MSCI EM), EPU index (Hong-Kong based) (left axis, black) and real residential property prices index (right axis, grey), 1-2011 - 9-2018.



(b) Original data of SRISK (MSCI EM, right axis, grey), Traditional shadow banking and Bank Shadow (left axis, black), 1-2011 - 9-2018

FIGURE 4

Variable	AR Model	Lags	**Test statistic**	**Test stat. (1st diff.)**	1% c.v	5% c.v	10% c.v
SRISK	Drift and det. trend	1	-3.062	-6.701	-4.066	-3.462	-3.157
EPU	Drift and det. trend	2	-2.327	-6.750	-4.067	-3.462	-3.157
PROPP	No drift, no det. trend	1	0.6502	-2.6502	-2.592	-1.945	-1.6139
TRADSB	Drift and det. trend	1	-1.2370	-4.4129	-4.066	-3.462	-3.157
BSHADOW	Drift and det. trend	1	-3.2560	-6.4496	-4.066	-3.462	-3.157

TABLE 2
Augmented Dickey - Fuller tests

Note: All series in natural logarithms. SRISK is in billion $US, EPU is Hong Kong based EPU index, PROPP is the real residential property price index (monthly after cubic interpolation). EPU and PROPP indexed at January 2011. Lags based on correlogram of residuals.

Variable	Model	Lags	Rank	**Trace statistic**	1% c.v	5% c.v	10% c.v
SRISK - EPU	Intercept, no det. trend	0	0	23.944	25.085	20.262	17.981
			1	6.521	12.761	9.164	7.557
SRISK - PROPP	Intercept, no det. trend	2	0	15.504	19.940	15.495	13.423
			1	1.415	6.635	3.842	2.706
SRISK - TRADSB	Intercept, det. trend	0	0	98.446	31.153	25.872	23.343
			1	8.925	16.557	12.517	10.666
SRISK - BSHADOW	Intercept, det. trend	1	0	16.669	19.940	15.495	13.430
			1	2.346	6.635	3.842	2.706
SRISK - EPU - PROPP	Intercept, det. trend	0	0	39.862	41.192	35.193	32.270
			1	17.124	25.085	20.262	17.981
			2	5.158	12.761	9.164	7.557
SRISK - EPU - PROPP - TRADSB	Intercept, det. trend	2	0	48.177	54.685	47.856	44.493
			1	26.775	35.466	29.798	27.066
			2	10.475	19.940	15.495	13.430
			3	0.184	6.635	3.842	2.706
SRISK - EPU - PROPP - BSHADOW	Intercept, det. trend	2	0	54.369	61.265	54.078	50.525
			1	30.163	41.192	35.193	32.270
			2	14.415	25.085	20.262	17.981
			3	5.633	12.761	9.164	7.557

TABLE 3
Unit root and cointegration tests

Note: Lags based on Akaike, Hannah-Quinn and Schwarz Information Criteria on the vector- error correction model. Trends/ intercepts based on regressions on the residuals of the cointegrating relationship.

Panel A: VECMS in pairs of series

Dependent Variable	SRISK ECT	SRISK Lagged term	PROPP ECT	PROPP Lagged term	TRADSB ECT	TRADSB Lagged term	BSHADOW ECT	BSHADOW Lagged term	EPU ECT	EPU Lagged term
SRISK			-0.124	6.666	-0.148	0.681	-0.234	-0.116	-0.001	0.091
			(0.002)***	(0.087)*	(0.011)**	(0.497)	(0.000)***	(0.874)	(0.038)**	(0.028)**
PROPP	0.000	0.000			-0.023	0.011	-0.015	0.002		
	(0.917)	(0.983)			(0.014)**	(0.584)	(0.022)**	(0.733)		
TRADSB	0.009	-0.009	-0.014	-0.034						
	(0.000)***	(0.017)**	(0.584)	(0.837)						
BSHADOW	0.012	0.004	-0.014	-0.617						
	(0.113)	(0.773)	(0.841)	(0.283)						
EPU	-0.006	-0.136								
	(0.001)***	(0.612)								

Panel B: SRISK - PROPP - EPU

	SRISK	EPU	PROPP	ECT
SRISK		0.114	7.724	-0.057
		(0.005)***	(0.062)*	(0.004)***
EPU	-0.065		-1.391	-0.194
	(0.538)		(0.897)	(0.000)***
PROPP	0.000	0.000		0.000
	(0.944)	(0.978)		(0.543)
TRADSB				
BSHADOW				

Panel C: SRISK - PROPP - EPU - TRADSB

	SRISK	EPU	PROPP	TRADSB	ECT
SRISK		0.088	5.266	1.103	-0.043
		(0.022)**	(0.19)	(0.276)	(0.003)***
EPU	0.002		-7.295652	-1.96602	-0.058
	(0.995)		(0.508)	(0.478)	(0.14)
PROPP	0.000	0.000		-0.006	-0.000
	(0.820)	(0.615)		(0.678)	(0.24)
TRADSB	-0.009	-0.000	-0.077		0.003
	(0.027)**	(0.615)	(0.600)		(0.000)***
BSHADOW					

Panel D: SRISK - PROPP - EPU - BSHADOW

	SRISK	EPU	PROPP	BSHADOW	ECT
SRISK		0.114	5.044	0.306	-0.101
		(0.004)***	(0.181)	(0.477)	(0.001)***
EPU	-0.016	-3.741	-0.882	-0.257	
	(0.953)		(0.709)	(0.440)	(0.001)***
PROPP	-0.000	0.000		0.005	0.000
	(0.993)	(0.815)		(0.495)	(0.695)
TRADSB					
BSHADOW	-0.015	-0.012	-0.604		0.015
	(0.327)**	(0.046)**	(0.267)		(0.001)***

TABLE 4
VECM results in pairs of variables

Note: Panel A: All models with constant and 2 lags, apart from SRISK - BSHADOW (3 lags), PROPP - TRADSB (trend). Panels B and C: 2 lags with trend. Panel D: 2 lags with no trend. All lags from AIC, BIC and Schwarz criterion. p-values in parentheses. Statistical significance at 1%, 5% and 10% denoted by (*), (**) and (***) respectively. All models have one cointegrating relationship and the lagged terms are depicted horizontally.

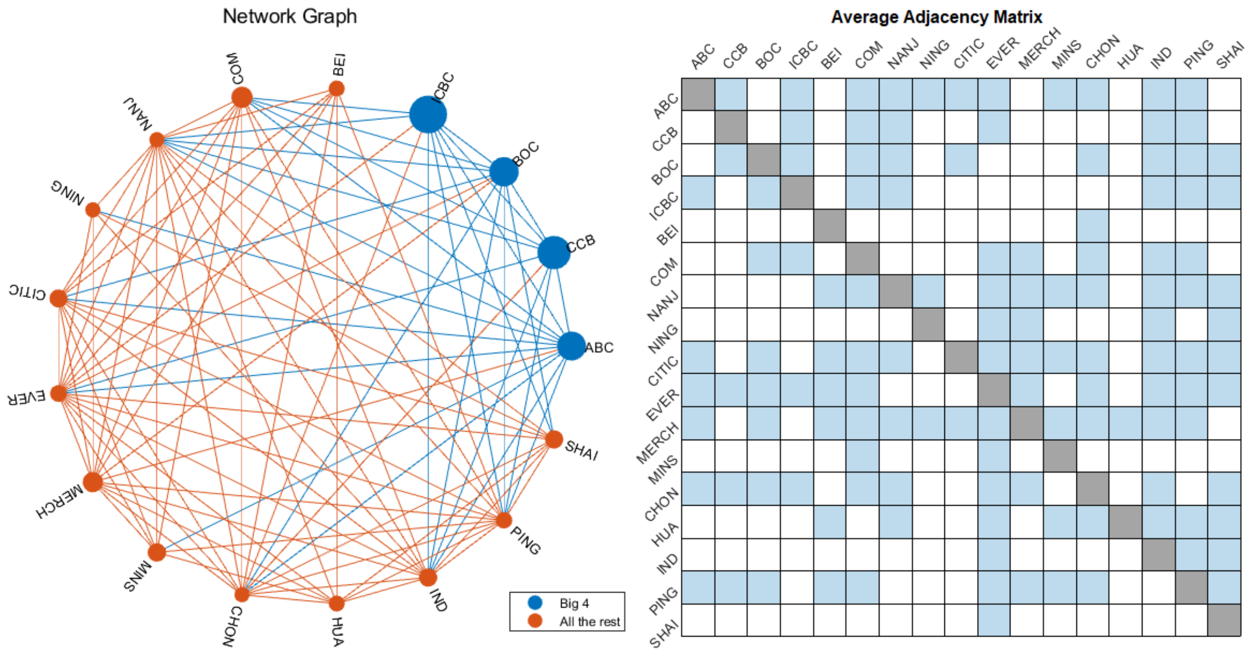
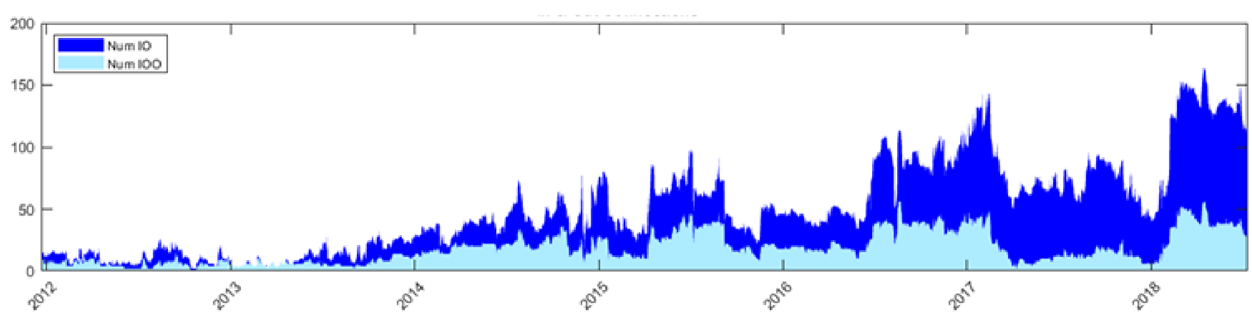


FIGURE 5
Interconnectedness network of Granger-caused connections and average adjacency matrix, 2011 - 2018. Blue cells denote causality from bank X to other banks (rows) and from other banks to bank X (columns).

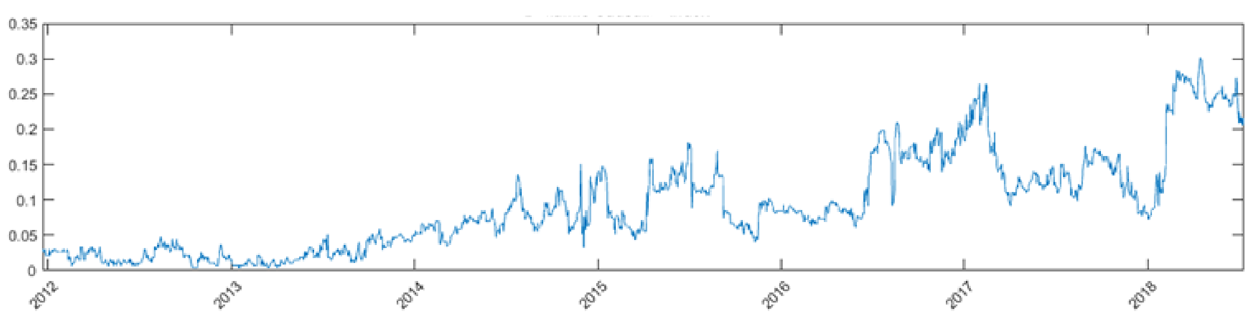
Bank	Granger-caused connections	Total net connections	Ranking (total net connections)	Ranking (Granger-caused)
Bank of Beijing	1	7	16	=16
Shanghai Pudong Bank	1	10	=11	=16
Minsheng Bank	2	8	15	15
Industrial Bank	3	12	=6	14
Bank of Ningbo	4	6	17	13
China Construction Bank	6	9	14	12
Bank of Communications	7	12	=6	=10
Industrial Commercial Bank of China	7	10	=11	10
Huaxia Bank	8	9	13	9
Bank of China	9	11	=10	8
Bank of Nanjing	10	16	=1	=5
Chongqing Bank	10	14	4	=5
Ping An Bank	10	15	3	=5
Agricultural Bank of China	11	12	=6	=3
China Everbright Bank	11	16	=1	=3
China CITIC Bank	12	12	=6	2
China Merchants Bank	13	13	5	1

TABLE 5
Network degree centrality results, 2011 - 2018

Note: Number of connections and firm ranking for Granger-caused connections and the total number of connections. The equality sign denotes the same number of connections between multiple banks.



(a) In+Out (IO) and In+Out-Others (IOO) connections over time



(b) Dynamic Causality Index

FIGURE 6

Bank	**Granger causality**	**Bank**	**Granger causality**
China Construction Bank		China CITIC Bank	$\rightarrow$ (***)
Bank of Communications		Bank of Beijing	$\rightarrow$ (***)
Huaxia Bank	$\rightarrow$ (***)	Bank of Nanjing	
Ping An Bank	$\rightarrow$ (***)	Bank of Ningbo	
Shanghai Pudong Bank	$\leftarrow$ (*)	Industrial Bank	$\leftrightarrow$ (***)
China Merchants Bank	$\rightarrow$ (*)	Minsheng Bank	$\leftarrow$ (***)
Bank of China	$\rightarrow$ (***)	Agricultural Bank of China	$\rightarrow$ (*)
Industrial Commercial Bank of China	$\rightarrow$ (***)	Chongqing Bank	$\rightarrow$ (***)

TABLE 6
SRISK Granger causality between Everbright and all other banks

Note: Granger causality between the SRISK monthly time series (first differences) of Everbright and all other banks for January 2011 - September 2018. ($\rightarrow$) denotes causality from Everbright towards a bank, ($\leftarrow$) denotes causality from a bank towards Everbright, ($\leftrightarrow$) denotes bi-directional causality, blank denotes no causality. Statistical significance reported at 1% (***), 5% (**), 10% (*)

Appendix A. Results using the MSCI EM market index and A-shares.

The varying restrictions on foreign investments in the Chinese equity market during the period we cover raise concerns about the effect of market integration on our results. International marginal investors which allocate wealth across emerging markets would not use a Chinese index as performance benchmark, while domestic investors may be exposed to systemic risk to a different extent. We expand our analysis on systemic risk from the domestic case in two ways. First, we follow Engle et al. (2014) and use a relevant international index, the MSCI EM index, to examine the contribution of the Chinese banking sector to its systemic risk. We employ a more suitable -10% monthly distress threshold and H-shares, where applicable[7]. Effectively, we shift the focus from domestic to international investors and on whether their concerns on systemic risk in the Chinese banking sector are similar.

The evolution of aggregate SRISK based on the MSCI EM benchmark is virtually identical to aggregate SRISK under the domestic index for -10% and -30% thresholds (Figures 1a, A.7a). The correlations between the alternative SRISK estimates range between 96.4% and 99.5%, indicating that our results are robust to alternative assumptions about the level of integration of the Chinese equity market. Thus, a change of benchmark does not affect our conclusions on systemic risk and causality and the benchmarks can be used interchangeably.

[INSERT FIGURE A.7 HERE]

Although the magnitude of aggregate SRISK is not significantly affected by a change in the market benchmark, the SRISK distribution between the Big 4 and all other banks changes when the MSCI EM index is used. The Big 4 contribute more to total SRISK in percentage and absolute terms (Figures A.7b, A.8a) but at a declining share. Their contribution peaks at USD 540 billion, while all other banks combined peak at USD 340 in early 2018. Crucially, the contribution of the Big 4 gradually decreases in 2011-2018 while the contribution of all other banks increases, leading to a 60-40% split in 2018. This is to

[7]The results for the domestic case under a -10% distress threshold are very similar to the base case and are omitted. They are available upon request

be expected, because the Big 4 are globally important financial institutions with a much greater international footprint than the smaller banks.

[INSERT FIGURE A.8 HERE]

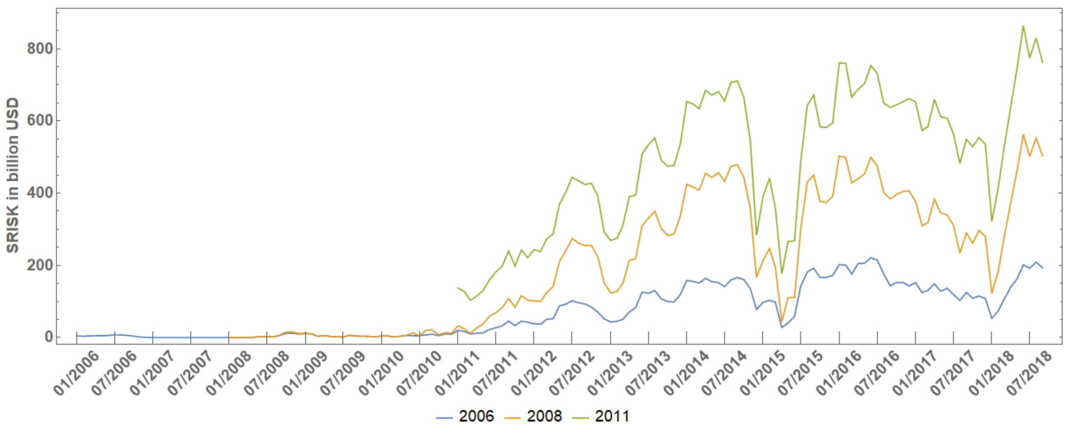
It is important to emphasize, however, that their reducing share (an increasing share for smaller banks) highlights the increased importance of the wider banking sector rather than an improvement of the risk exposure of its flagship institutions. The increasing SRISK contribution of smaller banks becomes more obvious in recent years. In the domestic case, the smaller banks appeared to be just as influential. In the international case, we observe the same result since their share is very close to that of the Big 4. Thus, the same intuition holds for both cases, with banks beyond the biggest firms exerting considerable influence on the riskiness of the financial system. ABC again contributes most to systemic risk (Figure A.8b), as it is both the bank with the highest SRISK and the one with the most SRISK fluctuations. ICBC and CCB move at the same levels and follow the pattern most of the time after 2011.

Figure A.9 shows the contribution of all banks to total SRISK in 2012-2018 (December values). The results strengthen the insights gained from the aggregate trends, as they appear to hold for individual banks as well. While the SRISK of ABC dominates every year, the contribution of the other three biggest banks is again considerable. The contribution of smaller banks constantly increases as a total but, individually, they generally contribute below 7-8%. A percentage increase implies a shifting of risk across banks but does not prevent a reduction of systemic risk in total, which is in line with our interconnectedness results. Overall, the largest institutions are the main contributors of systemic risk with many smaller banks contributing to a lesser but increasing degree on aggregate in recent years.

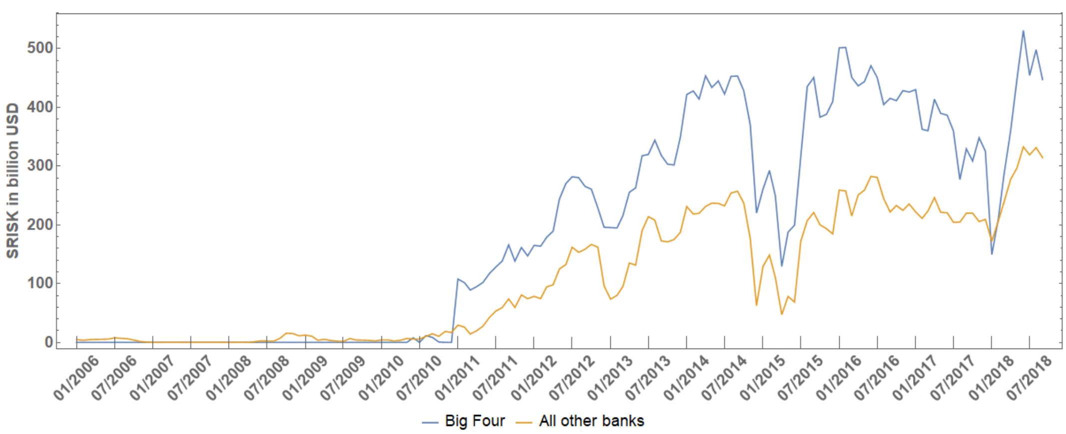
[INSERT FIGURE A.9 HERE]

We also revisit our results in Section 4.2, which relied on aggregate SRISK based on the MSCI EM index under a -10% distress threshold. We perform the same estimation using aggregate SRISK under the domestic index with a -30% distress threshold. The VECM results in Table A.7 are largely consistent with the results in the main paper. Our key findings on EPU, housing prices and shadow banking affecting SRISK in the long run are unaltered. Nevertheless, the statistical significance of some short-run causality estimates decreases. This does not alter the main intuition of our findings, and the causal relationships we observe between our variables are robust to changes in the market index, the type of shares selected and the distress threshold set.

[INSERT TABLE A.7 HERE]

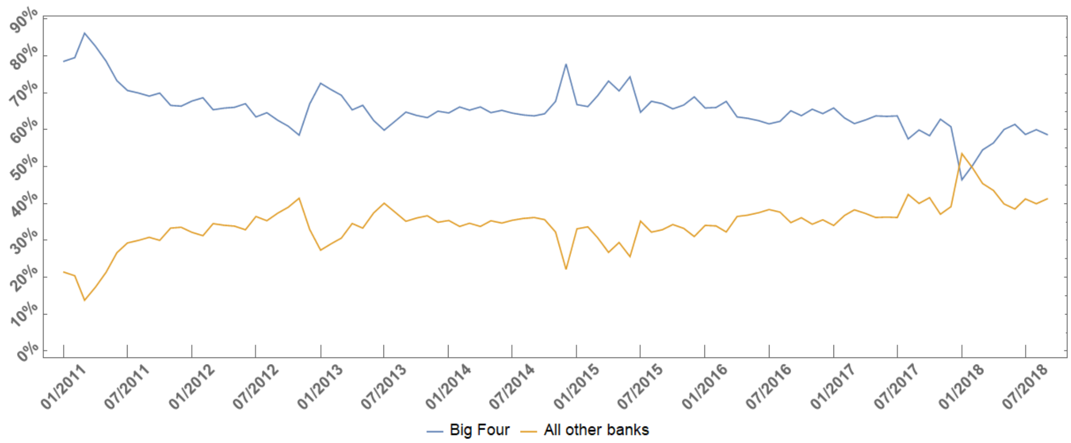


(a) Aggregate SRISK (MSCI EM) per entry year. 2006: CCB, BoComms, Huaxia, Ping An, Shanghai Pudong. 2008: BoC, ICBC, Merchants, CITIC, Beijing, Nanjing, Ningbo, Industrial. 2011: Minsheng, ABC, Everbright, Chongqing

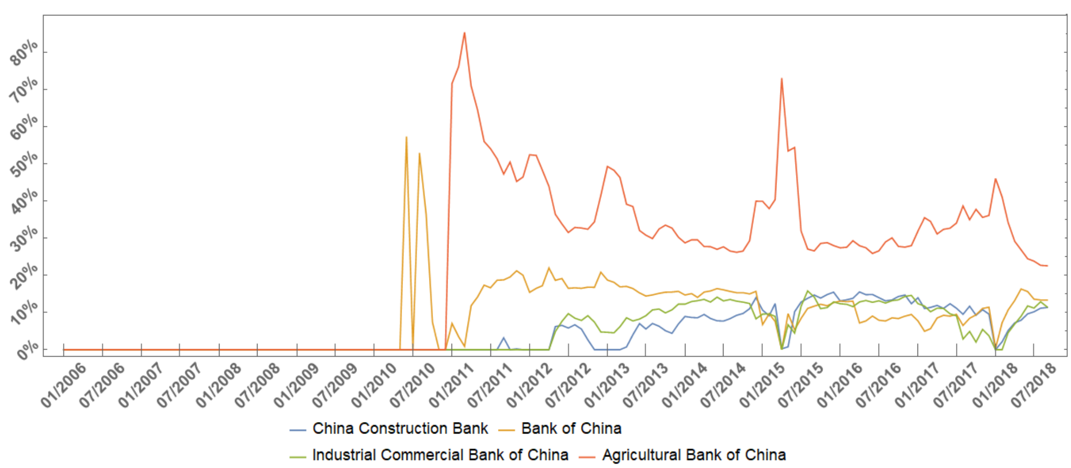


(b) Aggregate SRISK (MSCI EM) of the Big Four (CCB, BoC, ICBC, ABC) and all other banks

FIGURE A.7



(a) Contributions (%) to aggregate SRISK (MSCI EM) of the Big 4 and all other banks



(b) Contribution (%) of each of the Big Four banks to total SRISK (MSCI EM)

FIGURE A.8

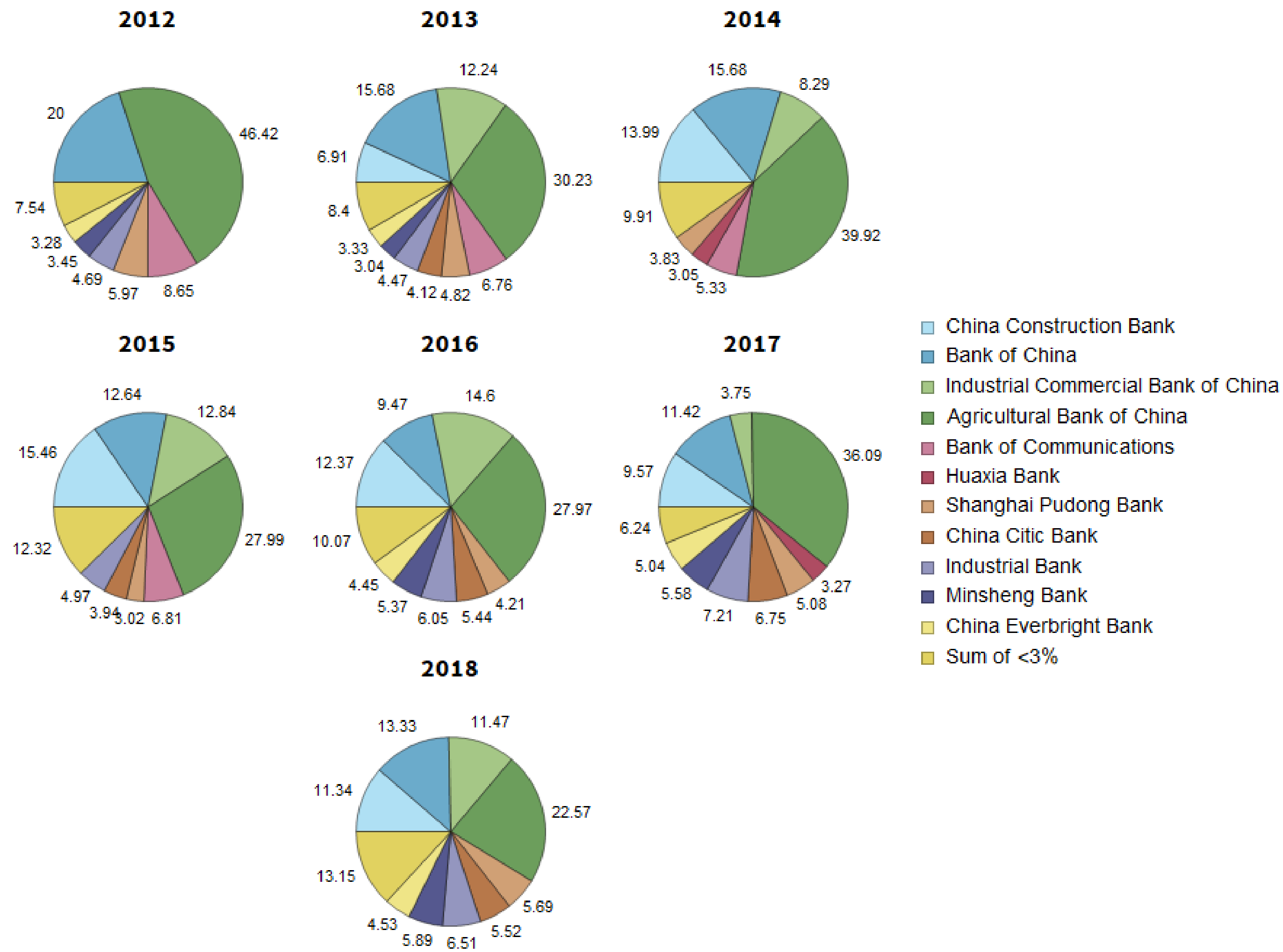


FIGURE A.9
Percentage contribution to aggregate SRISK for the MSCI EM index with 10% distress threshold, December 2012 - 2018

VECMs in pairs

SRISK as Dept. variable	ECT	1st lag	2nd lag	**SRISK as Ind. variable**	ECT	1st lag	2nd lag
EPU	-0.140	0.060	-0.145	EPU	0.004	0.118	0.376
	(0.002)***	(0.549)	(0.139)		(0.919)	(0.214)	(0.000)***
PROPP	-0.187	-0.680	1.880	PROPP	0.000	0.000	-0.001
	(0.000)***	(0.499)	(0.060)*		(0.716)	(0.971)	(0.032)**
TRADSB	-0.237	-4.157	0.362	TRADSB	0.002	-0.001	-0.000
	(0.000)***	(0.559)	(0.959)		(0.107)	(0.426)	(0.897)
BSHADOW	-0.226	-0.879	0.484	BSHADOW	0.006	-0.006	-0.002
	(0.000)***	(0.636)	(0.788)		(0.060)*	0.292	0.732

SRISK - EPU - PROPP, 1 cointegrating relationship

		SRISK		EPU		PROPP	
	ECT	1st lag	2nd lag	1st lag	2nd lag	1st lag	2nd lag
SRISK	-0.188			0.100	0.029	2.147	6.972
	(0.000)***			(0.015)**	(0.474)	(0.760)	(0.321)
EPU	-0.192	0.317	0.873			-15.657	0.978
	(0.082)*	(0.204)	(0.000)***			(0.345)	(0.953)
PROPP	0.000	0.000	-0.002	0.000	-0.000		
	(0.916)	(0.816)	(0.150)	(0.897)	(0.772)		

SRISK - EPU - PROPP - TRADSB, 1 cointegrating relationship

		SRISK		EPU		PROPP		TRADSB	
	ECT	1st lag	2nd lag	1st lag	2nd lag	1st lag	2nd lag	1st lag	2nd lag
SRISK	-0.011			0.050	-0.002	3.546	4.865	-6.907	5.596
	(0.038)**			(0.236)	(0.960)	(0.634)	(0.512)	(0.023)**	(0.058)*
EPU	-0.009	0.093	0.630			-12.958	-1.023	-8.862	2.868
	(0.434)	(0.733)	(0.014)**			(0.439)	(0.951)	(0.196)	(0.666)
PROPP	0.000	0.000	-0.003	0.000	0.000			-0.077	0.086
	(0.285)	(0.667)	(0.130)	(0.867)	(0.944)			(0.079)*	(0.045)**
TRADSB	-0.001	0.000	0.000	0.000	0.001	-0.080	0.061		
	(0.007)***	(0.917)	(0.915)	(0.513)	(0.356)	(0.755)	(0.812)		

SRISK - EPU - PROPP - BSHADOW, 1 cointegrating relationship

		SRISK		EPU		PROPP		BSHADOW	
	ECT	1st lag	2nd lag	1st lag	2nd lag	1st lag	2nd lag	1st lag	2nd lag
SRISK	-0.177			0.111	0.037	2.043	3.810	0.288	0.303
	(0.000)***			(0.009)***	(0.364)	(0.770)	(0.588)	(0.697)	(0.672)
EPU	-0.161	0.323	0.747			-8.328	-2.247	0.889	-2.941
	(0.115)	(0.205)	(0.002)***			(0.609)	(0.891)	(0.605)	(0.077)*
PROPP	0.001	0.000	-0.003	0.000	0.000			0.001	0.001
	(0.430)	(0.987)	(0.089)*	(0.908)	(0.678)			0.946	0.937
BSHADOW	0.013	0.007	-0.015	-0.008	0.001	0.016	-0.591		
	(0.015)**	(0.614)	(0.229)	(0.119)	(0.823)	(0.985)	(0.493)		

TABLE A.7
Vector Error Correction estimates with the domestic index and 30% distress threshold (3 lags with trend). Statistical significance at 1% (***), 5% (**) and 10% (*)

Appendix B. Systemic risk and Chinese macroeconomic variables

The relationship between systemic risk and various domestic macroeconomic variables is a common topic in the early SRISK literature. Based on predictive regressions, Brownlees and Engle (2016) find some evidence that lagged values of SRISK affect industrial production in the USA, and Engle et al. (2014) find that SRISK Granger-causes industrial production , business confidence, the unemployment rate and producer inflation in a sample of 8 major European countries. Macro variables were also found to have feedback effects on SRISK, especially producer inflation. Although the question is not central to our paper, in this appendix we complement our analysis by inspecting the relationship between systemic risk in the Chinese banking system and three domestic macroeconomic indices obtained from FRED, available at monthly frequency between January 2011 and September 2018. These are the Monthly Index of Total Industrial Production Excluding Construction (CHNPRINTO01IXPYM), the Monthly Index of Seasonally Adjusted GDP Normalized for China (CHNLORSGPNOSTSAM) and the Monthly Seasonally Adjusted Ratio of Exports to Imports for China (XTEITT01CNM156S).

ADF and Phillips- Perron stationarity tests show that GDP and Total Industry have a clear downwards trend and some evidence of non-stationarity for the Exports to Imports Ratio. We can provide some insight by estimating pairwise VECMs in log scale. Table B.8 shows that there is long-term causality from all three macro variables to SRISK, but no short-term causality. The error correction terms remain statistically significant at 1% level but there are no statistically significant lagged terms. This shows that systemic risk in China reacts to changes in GDP, international trade and industrial production in the long-run, but the reverse is not true. We also detect an unstable long-run causal relationship from SRISK to the Exports to Imports ratio, where the ECM is positive and statistically significant. Our findings show that the systemic risk of the Chinese banking sector is affected by domestic macroeconomic variables but not vice versa. This shows that the Chinese banking sector is strongly affected by macroeconomic factors, especially industry related. We consider this evidence preliminary yet indicative and leave a more thorough discussion to future research.

Dependent variable	**Independent variable**	ECM	1st lag	2nd lag	3rd lag
SRISK	GDP	-0.174 (0.057)***	-821.443 (1930.169)	1632.660 (3656.929)	-829.495 1809.053
SRISK	Industrial Production	-0.199 (0.054)***	5.061 3.136	2.013 3.140	
SRISK	Exports to Imports ratio	-0.111 (0.042***)	-0.391 (0.225)*	-0.491 (0.200)*	
Exports to Imports ratio	SRISK	0.041 (0.021)**	-0.020 (0.052)	-0.161 (0.052)***	

TABLE B.8
Results of pairwise VECMs between SRISK and macroeconomic variables

Note: Statistically significant VECM estimations at the levels, with constant. Lags determined by the Bayesian, Schwarz and Akaike information criteria. Statistical significance at 1% (***), 5% (**) and 10% (*), standard errors in parentheses.

Appendix C. The role of government guarantees

A regulatory intervention worth discussing separately is the Deposit Insurance Act, introduced in May 2015. It is the first attempt to introduce a flat-rate deposit insurance scheme for commercial banks that was meant to replace prior implicit guarantees on bank bailouts. The scheme is described in detail in Yamori and Sun (2019); the scheme is compulsory and is operated by the People's Bank of China. It does not cover deposits at foreign branches of domestic banks and domestic branches of foreign banks but does cover all domestic and foreign currency deposits up to 500,000 RMB, including the principal and accrued interest per saver at each covered bank. The central government does not inject initial funds in the funding of the scheme. A flat-rate premium is used currently, and future funding of the deposit insurance scheme will use a combination of a benchmark premium rate and a risk-based one. Yamori and Sun (2019) find evidence that the introduction of the deposit insurance scheme has an adverse wealth effect on the banking industry in China and creates a redistribution of wealth from small to large banks. A further argument is that such a scheme increases the probability of default, since it no longer guarantees bailouts, and creates moral hazard on behalf of bank managers; because the premia are not risk-adjusted, the bank has an incentive to take excess risk (e.g. increase leverage) which turns the scheme into a form of subsidy.

We examine if such effects are present in our SRISK results for the Big 4 banks and all other banks by estimating a simple dynamic regression Markov switching model of the form

$$SRISK_t = \mu_{st} + \epsilon_t, \epsilon \sim N(0, \sigma^2)$$

where s is the state (regime) 1 or 2, μ the state dependent mean and ϵ_t the next period innovation which follows a normal distribution with zero mean and standard deviation σ. Models with state-dependent standard deviations and lagged values of SRISK performed more poorly, so for brevity we refer to the case above. The estimation provides values for σ (common for both states) and state means μ_1, μ_2, as well as the transition probabilities p_{ss} for moving from one state to the other. We opt for dynamic regression instead of autoregression because it is more suitable for monthly data and it allows for instant, rather than gradual, adjustments after a state change. The model is well-suited for our purposes as, unlike structural changes models, a Markov switching model admits only occasional and exogenous changes, not frequent changes at random time points. This allows us to address the issue of the effect of the government guarantees indirectly. The results can be found in Table C.9.

[INSERT TABLE C.9 HERE]

[INSERT FIGURE C.10 HERE]

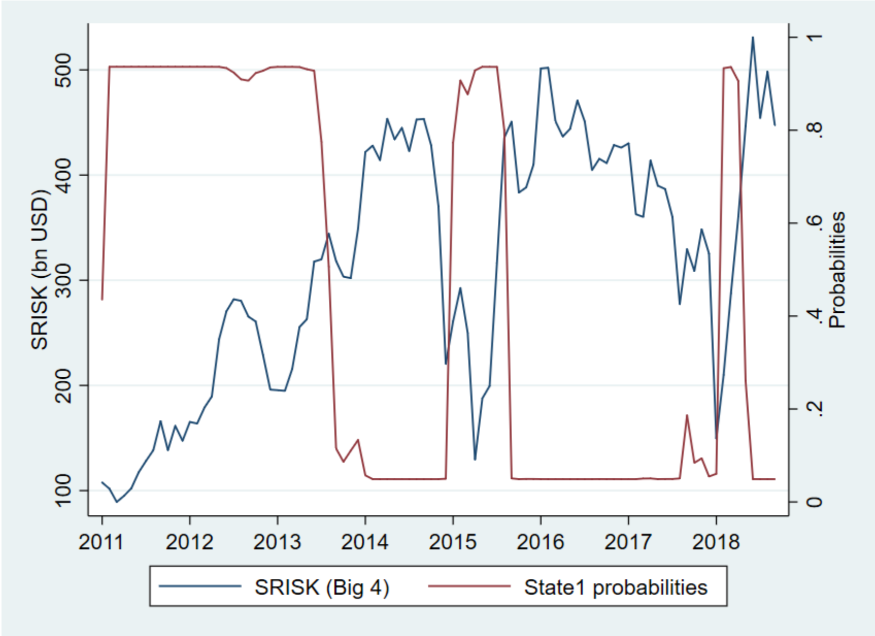
State 1 is the low mean state (195.230 for the Big 4, 90.767 for all other banks) and State 2 the high mean state (402.927 and 230.1 respectively). The mean values correspond to average SRISK for each state. The states are highly persistent, with $p_{11} = 0.936$ and $p_{22} = 0.951$ the probabilities to remain in the current state for the Big 4 and $p_{11} = 0.960$, $p_{22} = 0.971$ for all other banks. The probabilities to change state are $p_{12} = 0.064$ and $p_{21} = 0.049$ for the Big 4 and $p_{12} = 0.040$ and $p_{21} = 0.029$ for all other banks. The timings of the regime changes are identical for both cases, with the exception of a very brief switch in 2018 for the Big 4 (Figure C.10). The regime change with the most interest takes place in 2015, where right after the introduction of the Deposit Insurance Act SRISK rapidly increases and the state changes from low (State 1) to high risk (State 2). State 2 dominates until the end of the sample and covers the outbreak of the stock market turmoil and the sharp increase in systemic risk. Notably, it also dominates after mid-2013 and the 2015 State 1 period is quite brief. Although the introduction of government guarantees may be a reason for a regime change, such guarantees are not captured in the book value inputs of SRISK and may only be indirectly introduced by returns. Yamori and Sun (2019) do provide evidence towards that direction, and it can also be argued that the gradual increase in the systemic risk of smaller banks may be attributed to that factor. However, we treat our findings with caution and as indirect indicators rather than conclusive arguments. First, there are many more factors at play in the 2015 - 2018 period (shadow banking regulation, stock market crashes etc). Second, our framework does not explicitly capture government guarantees.

Panel A: Parameter estimates					
Big 4			All other banks		
μ_1	195.230	(10.526)***	μ_1	90.767	(7.115)***
μ_2	402.930	(8.679)***	μ_2	230.100	(5.590)***
σ	60.677	(4.612)	σ	41.307	(3.084)

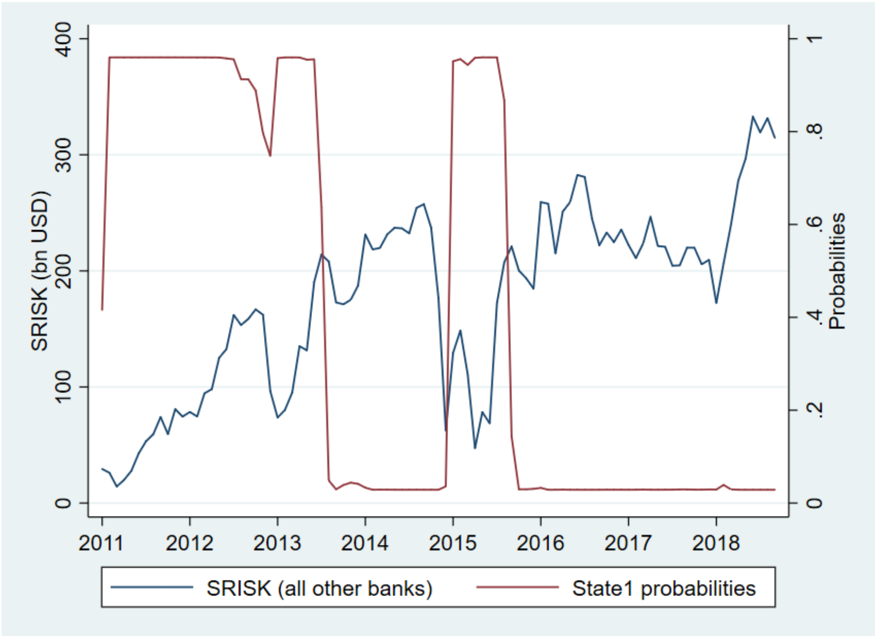
Panel B: Transition probabilities from (row) / to (column)					
Big 4			All other banks		
	1	2		1	2
1	0.936	0.064	1	0.960	0.040
2	0.049	0.951	2	0.029	0.971

TABLE C.9
Dynamic regression Markov switching results

Note: Statistical significance at 1% (***), 5% (**) and 10% (*). Parameter standard errors in parentheses. Each transition probability row denotes the probability to move from the respective state to each other, e.g. $p_{12} = 0.064$ is the probability to move from State 1 to State 2.



(a) SRISK and State 1 (low SRISK) probability plots for the four biggest banks



(b) SRISK and State 1 (low SRISK) probability plots for all other banks

FIGURE C.10