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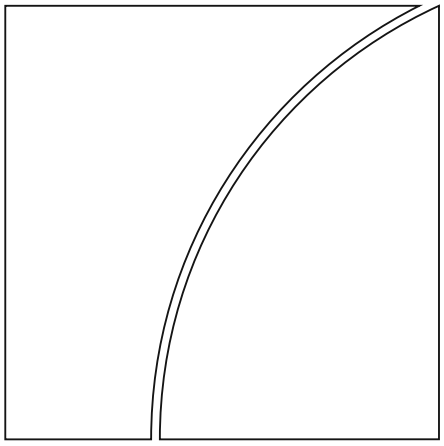

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by Amanda Liu, Jing Liu and Ilhyock Shim

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Shadow loans and regulatory arbitrage: evidence from China[1]

Amanda Liu, Jing Liu and Ilhyock Shim[2]

Abstract

This paper examines how Chinese banks used on-balance sheet shadow loans for regulatory arbitrage and whether the financial market priced in the banks' use of shadow loans and the resulting vulnerabilities in 2016–2020. It finds that banks chose to window dress their regulatory capital ratio by using shadow loans. It also shows that banks with a higher shadow loan ratio or a lower breakeven non-performing loan ratio obtained from reverse stress testing faced higher wholesale funding costs. Finally, after the announcement of a rare bank failure event, more vulnerable banks witnessed lower cumulative stock and bond returns.

Keywords: bank capital regulation, Chinese economy, regulatory arbitrage, shadow banking, reverse stress test.

JEL classification: G12, G14, G21, G28.

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[2] Amanda Liu is Senior Research Analyst, Monetary and Economic Department, Bank for International Settlements (BIS), email: amanda.liu@bis.org.
Jing Liu is Senior Economist, Greater China, HSBC Hong Kong, email: jing.econ.liu@hsbc.com.hk.
Ilhyock Shim is Head of Economics and Financial Markets for Asia and the Pacific, Monetary and Economic Department, BIS, email: ilhyock.shim@bis.org.

1. Introduction

China's shadow banking sector has grown rapidly since the Great Financial Crisis (GFC) in 2008–9. Similar to the western counterparts, China's financial regulators have in response raised concerns over the fast-growing sector as shadow banking has been used for regulatory arbitrage and increased the overall leverage of the financial system. Unlike the western counterparts, however, China's shadow banking centres around the banking system, because commercial banks dominate shadow banking activities. Hence, Ehlers et al (2018) and Sun (2019) coined the term "shadows in the bank". This paper focuses on shadow loans on the balance sheets of Chinese banks.

Despite multiple attempts by China's financial regulators to contain the growth of shadow banking, Chinese banks' shadow banking activities continued to rise until 2018. Anecdotal evidence suggests that banks used alternative categories, such as repo and investment receivables, to circumvent regulatory limits on loan exposures and risk concentration.[3] Eventually the introduction of the Unified Rules for Asset Management (the Rule) in April 2018, a joint effort by China's financial regulators, slowed down the build-up of risks, as evidenced by the negative growth of shadow banking activities (ie the sum of the outstanding amount of trust loans, entrusted loans and undiscounted banker's acceptance bills) in total social financing (TSF) from 2018 onwards.

This paper investigates how the shadows in the bank evolved alongside the tighter regulation in China. We address this question by directly using shadow loans on banks' balance sheets. We first ask whether on-balance sheet shadow loans are used for regulatory arbitrage; that is, to what extent banks manage to hide risk associated with shadow loans. Then we ask if the financial market in China prices in risks associated with shadow loans. In particular, we ask if banks relying heavily on shadow loans manage to keep funding costs from rising, and if investors in equity and bond markets require higher returns for more vulnerable banks.

We show three key results in this paper. First, the ratio of a bank's shadow loans to its net worth (ie equity) is negatively correlated with its leverage ratio, calculated by dividing the bank's regulatory capital by its total assets, and the correlation is statistically significant. In contrast, the relationship between a bank's shadow loan ratio and its (regulatory) capital adequacy ratio, defined as the bank's capital as a ratio of its risk-weighted assets (that is, a risk-weighted capital ratio), is not statistically significant. Our results suggest that banks choose to window dress its regulatory capital ratio by using shadow loans.

Second, banks with higher shadow loan ratios face higher funding costs in the wholesale market. The reason is simple: Chinese banks structure shadow loans in collaboration with other financial institutions. These very "partners" are active investors in the interbank market. Banks may be able to hide their vulnerability from the regulators temporarily, but still leave the smoking gun evidence, and hence must pay risk premium on the market. The results are robust for banks with lower breakeven non-performing loan (NPL) ratios. This ratio is derived from a reverse stress test on banks' vulnerability incorporating shadow loans. However, banks with higher

[3] A risk concentration refers to an exposure that may arise within or across different risk categories with the potential to produce losses large enough to threaten an institution's health or ability to maintain its core operations or a material change in the institution's risk profile (Joint Forum (1999) and CEBS (2010)).

regulatory NPL ratios do not necessarily pay a higher funding cost on the wholesale market. This difference in results is partly driven by regulatory arbitrage of banks, where the variability in NPL ratios is supressed, muffling up the real credit risk.

Last, we test the market response to the Baoshang Bank regulatory takeover. Relatively more vulnerable banks, measured either by higher shadow loan ratios or lower breakeven NPL ratios, witnessed lower cumulative returns on both the equity market and the bond market. However, when we use regulatory NPL ratios as the measure, the relationship is not statistically significant.

This paper is related to three strands of literature, one on China's shadow banking, another on bank stress testing, and the third on securitisation.

First, the growing literature on China's shadow banking shows that the distinctive feature of China's shadow banking is the dominant role of banks (Ehlers et al (2018) and Sun (2019)). In particular, Ehlers et al (2018) provide a stylised shadow banking map to describe the complex interlinkages, while Sun (2019) proposes a bottom-up approach to measure banks' shadows. Chen et al (2018) establish empirical evidence that the rapid rise of shadow banking activities was caused by contractionary monetary policy during 2009–2015. Banks circumvented the regulatory restrictions by off-balance sheet lending, as well as by classifying risky assets on their balance sheets under non-loan categories. In particular, banks packaged loans as investment receivables in collaboration with channelling intermediaries, mainly to facilitate regulatory arbitrage. Shadow loans had made banks less resilient due to banks' over-concentration of risks and inadequate provisioning. Cheng and Wang (2020) show that, with the asset management regulation introduced in 2018 focusing on bank-issued wealth management products (WMPs), the effectiveness of the transmission of monetary policy improved as banks gradually moved off-balance sheet WMPs back onto the balance sheet. In particular, they find that the results are pronounced for joint-stock commercial banks. However, the literature does not explore whether the financial market prices in banks' hidden risk as reflected by their funding costs.

More recent papers show that China's shadow banking sector provides loans to certain sectors or projects which traditional banks do not fully support. Allen and Gu (2020) explain that China's shadow banking has grown rapidly in the last decade driven by the regulatory burden in the traditional banks as well as the credit constraints in certain restrictive areas, and argue that implicit guarantees on shadow banking from banks, nonbanks or governments might provide a second-best arrangement in funding risky projects and improving welfare. Zhu (2021) also points out that shadow banking in China arose from the need to get around various lending restrictions imposed by the central government on banks, but shows that in recent years, shadow banking loans had a positive effect on real estate investments only, and their effects on investments by private firms outside the real estate sector had been negative.

Our research is also related to the rich literature on bank stress testing.[4] Stress testing is widely adopted by bank supervisors to assess the impact of potential risks on the financial system as well as vulnerabilities of supervised institutions, and by financial institutions as risk management tools. There are a variety of stress tests to suit varied settings, so their methodologies vary in terms of objectives, time horizon, focal risks to analyse, the level of granularity, etc. Traditional stress tests start with a design of stress scenarios, such as a macroeconomic shock to the system, and explore

[4] The Basel Committee on Banking Supervision (BCBS) published a comprehensive review of the supervisory and bank stress testing practices (BCBS (2017)).

how the shock can impact financial institutions, say, whether the institutions have enough capital to withstand the rising defaults resulting from the negative shock. In contrast, reverse stress test is a different breed. It starts with the result and works backward to produce a scenario that will cause the specified adverse outcome. It is often used as a complementary test to the traditional stress tests (BCBS (2017), European Banking Authority (2018) and Financial Conduct Authority (2020)).

Reverse stress tests are useful when data quality is weak (Ong et al (2014)). We adopt this method in the paper when measuring how the presence of shadow loans influences a bank's vulnerability to adverse shocks. We start with the scenario where the capital adequacy ratio drops to the regulatory minimum due to the shock, and compute what level of the NPL ratio can bring such a change. We also assume that shadow loans will need to be re-categorised as official loans and become subject to the same regulatory restrictions, such as loan categorisation and provisioning, risk weights etc, by the end of the testing period. Shadow loans and the reverse stress testing breakeven NPL ratio (RNPL ratio) are used as key variables to study why banks engage in shadow businesses and whether they manage to get away from higher funding costs by creating shadow loans, respectively.

Finally, this paper is related to the securitisation literature in answering the funding cost question. Casu et al (2013) show that even though securitising banks tended to be more profitable before the GFC, they had higher credit risk exposure and faced higher funding costs.[5] Acharya et al (2013) study a subset of securitisation used for regulatory arbitrage. Contrary to the typical perception that securitisation transfers risks, in the period leading up to the GFC, some banks designed securitised products for regulatory arbitrage while retaining risks on their balance sheets. Asset-backed commercial paper (ABCP) conduits were one such example. Acharya et al (2013) document that the relative size of a bank's conduit exposure explains the extent of stock price deterioration of the bank when the crisis broke out. Relatedly, ABCP spreads increased, and the issuance amount decreased, which was more so for those sponsored by weaker banks, when the run started on ABCPs. We analyse the incentives and consequences of the on-balance sheet shadow loan creation by Chinese banks. Despite the seeming uniqueness of the so-called shadows in the bank, essentially Chinese banks are motivated by regulatory arbitrage, just as why western banks sponsored ABCP conduits pre-GFC. For this very reason, relatively weaker banks, or banks facing tighter capital constraints, are more likely to engage in such activities. We also show that weaker banks experienced larger equity and bond price drops after one rare bank restructuring event in China. We contribute to this strand of literature by showing that the essence of regulatory arbitrage remains the same despite the variety of forms. This finding to some extent challenges the conventional view that China's shadow banking is unique and should be analysed in a new framework.

The rest of the paper is organised as the following. Section 2 introduces the institutional background and explains how we obtain information of on-balance sheet shadow loans for our sample banks and calculate the RNPL ratio. Section 3 presents the empirical method, including hypotheses and empirical models. Section 4 shows the main results, while the appendix provides some robustness checks. Section 5 concludes.

[5] Dubecq et al (2015) document that pre-GFC, the US banking sector increased its exposure to credit risk and liquidity risk, but that the perceived riskiness of US financial intermediaries did not increase, and the effective level of banks' capital was difficult to assess during the period.

2. Background and data

2.1 Institutional background

China's shadow banking rose after the GFC and has been an area of concern for policy makers and academics in recent years. China rolled out the Four Trillion Stimulus Plan in November 2008, with some CNY 3 trillion funded by local governments, mainly in the form of bank loans via local government financing vehicles (LGFVs) given constraints on direct borrowing by governments that time. However, concerned about the rapid increase of LGFV borrowing and a potential build-up of risks, the central government reversed the ultra-easy credit policy, and the China Banking Regulatory Commission (CBRC) rolled out measures to restrict bank lending to LGFVs. Banks "creatively" moved LGFV loans to other categories on the asset side of their balance sheets to evade such a restriction. A similar trick was applied to other regulatory limits too, such as those guarding against large exposure and capital requirements. For example, loans had been packaged as repo assets until the practice was explicitly forbidden by Circular 127 issued by the financial regulators in May 2014.[6] Such regulatory arbitrage reduced the risk weights (from 100% for corporate loans to around 20% for repo assets), decreased capital requirements and helped banks circumvent adequate provisioning for loan losses. To some extent, shadow banking may have provided funding to borrowers who otherwise cannot access bank loans because market rates exceeded the regulatory upper bound of lending rates. However, individual banks may have engaged in excessive risk taking to pursue higher profits and built up vulnerabilities.

From the history of China's shadow banking, we can see the dominant role of banks. Shadow banking items appear both on- and off-balance sheets of banks originating loans. On-balance sheet shadow loans are disguised as investment receivables, while off-balance sheet shadow activities appear as banks' WMPs and asset management products by non-bank financial institutions. On- and off-balance sheet shadows may overlap. For example, when a bank collaborates with a broker to package shadow loans as a directional asset management product, these shadow loans are an asset item for the bank and a liability entry for the broker. The translucency and interlinkage of shadow banking activities make measurement of these activities challenging.

Concerned about the embedded vulnerabilities inside the banking system and potential systemic risk due to the complicated interlinkages among financial institutions, Chinese authorities have launched multiple policy measures against shadow banking activities. Early efforts targeted specific channels of shadow banking. For example, as early as August 2012 before the issuance of Circular 127, the CBRC urged banks to check the authenticity of interbank financing and stop hiding shadow lending under repo transactions. In response, banks chose other items, such as available-for-sale financial assets and investment receivables, to disguise shadow loans. A similar situation keeps resurging, which illustrates the caveat against channel-specific regulations. In April 2018, financial regulators in China jointly introduced the Rule, aiming to rein in shadow banking using an activity-based approach. In

[6] In May 2014, the People's Bank of China, the CBRC and three other financial regulators jointly issued the Notice on Regulating Interbank Business of Financial Institutions (State Council document no 127 or Circular 127). One important requirement is to exclude the "non-standard" debt assets, ie shadow loans, from the qualified underlying financial assets in repo business.

particular, the Rule set regulations on all kinds of asset management products overseen by different regulators, applying unified standards to leverage ratios, risk reserves, investment restrictions and other requirements. The Rule became effective immediately with the grace period set until end-2020 and later extended to end-2021 following the outbreak of Covid-19.

The Rule significantly slowed down the build-up of risks in the shadow banking sector. Based on the official statistics of TSF, the shadow banking components have decreased from CNY 23.4 trillion at end-2016 to CNY 22.3 trillion at the end of June 2020. A recent report on China's shadow banking by the China Banking and Insurance Regulatory Commission (CBIRC) estimates that the narrowly-defined shadow banking sector decreased from CNY 51.01 trillion at end-2016 to CNY 39.14 trillion at end-2019.[7] Similarly, if alternative measures on the size of the shadow banking sector in the literature on China's shadow banking are used, the same conclusion can be reached. In the next section, we will focus on on-balance sheet shadow loans of listed Chinese commercial banks, documenting how this shadow in the banks has evolved over time and affected banks' resilience. Shadow in the banks is even smaller than the CBIRC's "narrowly-defined" shadow banking sector, and does not go beyond banks' balance sheets.

2.2 Sample banks

Our sample includes 51 Chinese banks listed on the Shanghai, Shenzhen and Hong Kong stock exchanges, covering all large banks and most mid-sized banks. In terms of assets, the sample banks represent 85% of all commercial banks at end-June 2020 (Table 1).[8]

Total assets of sample banks as a percentage of each category of banks — Table 1

	State-owned banks	Joint-stock banks	City commercial banks	Rural commercial banks	All
2016	100%	94.20%	56.02%	8.45%	89.94%
2017	100%	94.54%	56.41%	8.65%	88.93%
2018	100%	95.19%	57.08%	8.77%	88.69%
2019	100%	95.40%	57.14%	9.04%	84.56%
2020 H1	100%	95.33%	57.33%	8.99%	84.58%

Sources: WIND; authors' calculations.

We download balance sheet data from banks' financial statements, and manually collect shadow loans from Notes to the financial statements. We follow the aggregation method of UBS (2017), where investment receivables in the forms of "trust beneficiary rights" and "directional asset management products" are added up across various items on the asset side. This method provides a more conservative estimate than the alternative deduction method of Sun (2019), as the latter essentially

[7] According to the CBIRC, the narrow definition of the shadow banking sector is the sum of interbank special purpose vehicle (SPV) investment, wealth management products invested in interbank wealth management products, non-standard debt assets and asset management products, entrusted loans, trust loans, hedge funds and P2P loans, after controlling double counting. See CBIRC (2020).

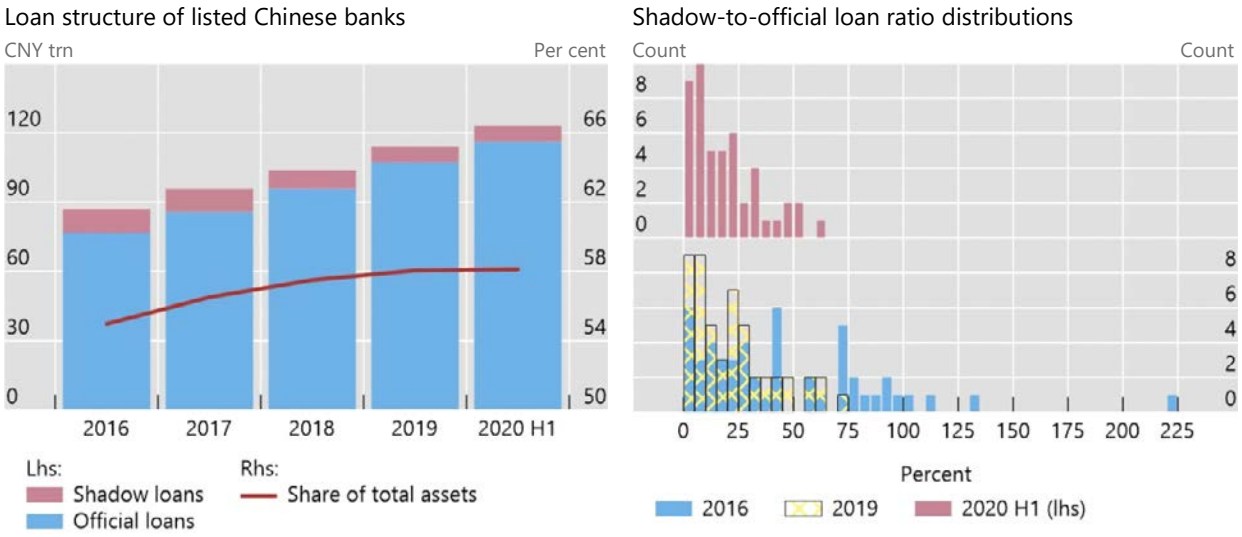
[8] Table A1 in the appendix provides the list of 51 banks in four categories.

treats all assets other than loans, foreign exchange and corporate bonds as shadow assets. Sun (2019) estimates that the shadow credits reached CNY 46.75 trillion at end-2016 using the deduction method. In contrast, the UBS (2017) estimate is much smaller at CNY 14.1 trillion when it applies the aggregation method to 237 banks.

The aggregate amount of shadow loans in our sample banks decreased by 35% from CNY 10.4 trillion at end-2016 to CNY 6.8 trillion at end-June 2020 (Graph 1, left-hand panel). At the individual bank level, shadow loans decreased for the majority of sample banks: the 2019 and H1 2020 distributions of the shadow-to-official loan ratio tilt towards lower values compared to the 2016 one (Graph 1, right-hand panel). Meanwhile, the total loan-to-asset ratio remained relatively stable (Graph 1, left-hand panel, red line), which suggests that the sample banks have substituted on-balance sheet shadow loans with on-balance sheet official loans in compliance with tightening regulation, since the first circulation of the Rule for public consultation in 2017.

Shadow loans[1] vs official loans in 51 banks in China

Graph 1



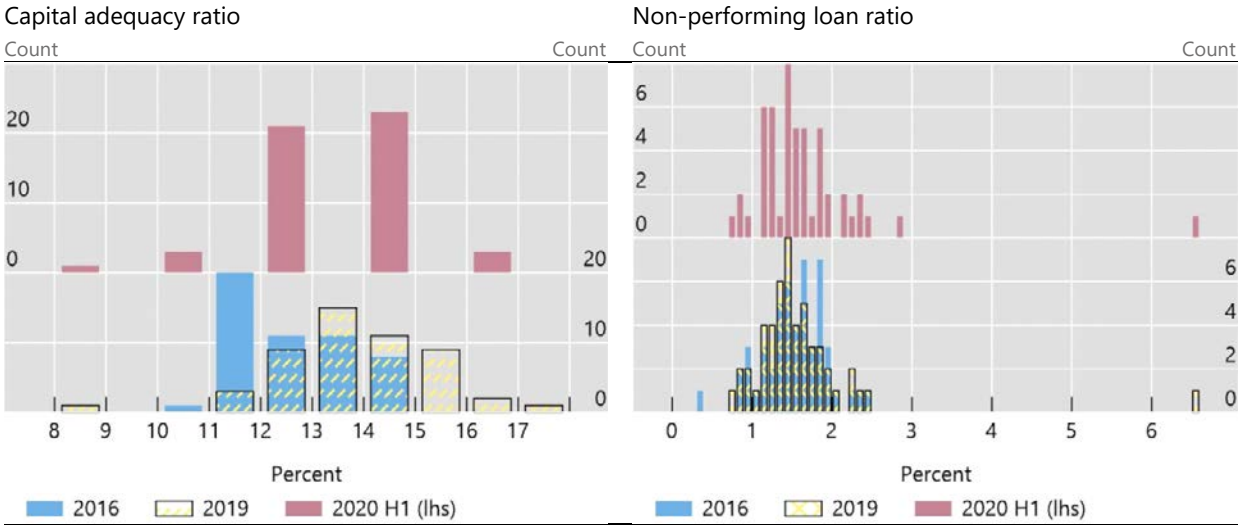
[1] On-balance sheet shadow loans are investment receivables in the forms of "trust beneficiary rights" and "directional asset management products" across various items on banks' asset side.

Sources: Annual reports of sample banks; authors' calculations.

In addition to swapping shadow loans for official loans, the sample banks seem to have fared better in terms of capital adequacy and asset quality in 2019 than in 2016, based on indicators such as the capital adequacy ratio (CAR) and the NPL ratio (Graph 2). Due to various regulatory forbearance in response to Covid-19, the impact of Covid-19 was not evident from the banks' balance sheet data, as the H1 2020 distributions of the CAR and the NPL ratios are similar to those of 2019.

However, such indicators cannot provide a reliable health check for banks, especially when they do not fully incorporate shadow loans. For example, Jinzhou Bank, which was restructured in 2019, appeared healthy in 2017 with the NPL ratio of 1.0% and the CAR of 11.7%, because its sizable shadow loans (equivalent to 161% of official loans) were not reflected in these indicators.

Distribution of capital adequacy and NPL ratios in 2016, 2019 and H1 2020 Graph 2



Sources: Annual reports of sample banks; authors' calculations.

2.3 Reverse stress testing breakeven NPL ratio

In this section, we develop a reverse stress test incorporating shadow loans to obtain a comprehensive resilience measure, namely the RNPL ratio. This ratio corresponds to NPL shocks that would deplete a bank's capital to a hurdle rate (such as the regulatory minimum), assuming that shadow loans are eventually (that is, at the end of the testing period) categorised as loans and comply with all regulatory capital requirements. We use reserve stress tests to quantify the effects of shadow loans on banks' resilience to adverse shocks.

We make the following key assumptions on our baseline case:

i. *The testing period is two years: year 1 is the business-as-usual scenario, where sample banks' net profits and the dividend pay-out ratio remain the same as year 0; the NPL shock materialises in year 2;*
ii. *The proportion of total loans to total assets and that of risk-weighted assets to total assets remain the same;*
iii. *Official loans grow 10% each year, while shadow loans remain the same in year 1;*
iv. *Shadow loans have the same credit quality as official loans; within each category (ie, performing or classified), loans follow the same migration matrix as that in year 0*[9]*; and*
v. *Banks maintain the minimum level of provisions in compliance with regulation.*

The above assumptions on the baseline case are close to stylised facts suggested by the data. For example, assumption (ii) is consistent with the pattern shown in the left-hand panel of Graph 1. Official loans grow 10% a year according to assumption (iii), which is roughly on par with the loan growth rate in recent years (10.2% in 2018 and 9.9% in 2019). Shadow loans are assumed to be flat before they are brought to light at the end of the testing period. We can change these assumptions as needed, such as a higher loan growth rate to reflect the heightened pressure on banks during

[9] Across-category moves, ie, from performing to non-performing, are reflected in the RNPL ratio.

Covid-19 (eg, loan extension as well as increased credit growth following the window guidance), or a worse credit quality of shadow loans.

Our reverse stress tests provide a comprehensive assessment of banks' viability by incorporating the impact of shadow loans, which the standard indicators such as the CAR and the NPL ratio may not be able to reveal. Take the example of Jinzhou Bank again: its 2017 RNPL ratio was only 1.49% despite the illusionary strength shown by the low NPL ratio (1.0%) and the reasonable CAR (11.7%). The low RNPL ratio suggests that Jinzhou Bank used shadow loans to cover its vulnerability.[10] The RNPL ratio varies across different types of bank. As of H1 2020, the five state-owned banks in the sample had the best results as their average RNPL ratio (9.58%) was above six times the headline NPL ratio (1.51%). The nine joint-stock banks had the worst results, with two sample banks having the RNPL ratio in the range between two and three times the headline NPL ratio as of H1 2020, five banks having the RNPL ratio in the range between one and two times the NPL ratio, and the remaining two banks having the RNPL ratio below the NPL ratio. Given that joint-stock banks represent over 20% of total assets of commercial banks, the results serve as a warning signal of potential vulnerabilities in the Chinese banking system rooted in some joint-stock banks.

3. Hypotheses development

In this section, we explore why banks utilised shadow loans and whether they managed to arbitrage capital regulation successfully and hide their vulnerabilities from investors.

It is well understood that bank capital regulation intends to prevent banks' excessive risk taking and reduce the cost of banks' failure to the banks' stakeholders and the society. The GFC illustrated how banks had engaged in shadow banking activities outside the radar of bank regulators, in order to maximise their profits at the cost to society. The more the banks can externalise the cost of their failure, the more incentives they have to conduct regulatory arbitrage (Acharya et al (2013)). In China, bank failure has been rare. Baoshang Bank is the first commercial bank which was liquidated through a judicial procedure. Other troubled banks (such as Hengfeng Bank, Jinzhou Bank and Bank of Gansu) were acquired by healthy banks or bailed out by state-owned enterprises under the guidance of financial regulators or governments. In this regard, Chinese banks may be incentivised to take risks. In the case of on-balance sheet shadow loans, risk exposure remains with the banks, so the main purpose is regulatory arbitrage.

China follows the Basel Core Principles for Effective Banking Supervision. Important principles on prudential regulations in relation to banks' solvency include capital adequacy, credit risk, problem assets, provisions and reserves. Anecdotal evidence suggests that banks package loans as shadows mainly to minimise regulatory capital requirements and circumvent requirements on risk concentration.

[10] Jinzhou Bank had shadow loans equivalent to 161% of the on-balance sheet official loans. They were recorded as "debt securities classified as receivables" and enjoyed a lower risk weight (as low as 25%, instead of the 100% weight as corporate loans). They were not subject the loan-provisioning rule either. Once we assume that shadow loans comply with the same regulatory requirements as official loans, Jinzhou Bank's vulnerability to adverse shocks becomes evident. Indeed, ad-hoc evidence confirms it: in 2018 and 2019, while the bank reduced its shadow-to-official loan ratio from 161% to 85% and 48%, respectively, the NPL ratio jumped from 1.0% to 5.0% and 6.5%, respectively.

Very few banks disclose details of their shadow loans, so our test will only focus on the part on capital requirements. Capital strapped banks package loans as "investment receivables" to reduce risk weighting, avoid provisioning requirements and window dress capital adequacy. Consequently, capital constraints are not reflected by the official CAR (the ratio of bank equity to risk-weighted assets), but rather by the leverage ratio (the ratio of bank equity to total assets). We therefore propose our first hypothesis:

Hypothesis 1: *Banks use on-balance sheet shadow loans for regulatory arbitrage.*

We test Hypothesis 1 with the following two regressions:

$$\textit{Shadow loan ratio} = \beta_0 + \beta_1 CAR + \beta_2(\textit{bank controls}) + \beta_3(\textit{bank-fixed effect}) + \varepsilon \quad (1)$$

$$\textit{Shadow loan ratio} = \beta_0 + \beta_1(\textit{leverage ratio}) + \beta_2(\textit{bank controls}) + \beta_3(\textit{bank-fixed effect}) + \varepsilon \quad (2)$$

We expect that the coefficient on the CAR, β_1, in equation (1) is not statistically significant, which implies a successful regulatory arbitrage by banks. In contrast, we expect that the coefficient on the leverage ratio, β_1, in equation (2) is negative and statistically significant, because capital constrained banks are more likely to engage in regulatory arbitrage by increasing shadow loans.

As discussed in the previous sections, banks engage third parties to set up shadow loans. For example, they interact with trust companies to channel trust beneficiary rights, and fund management companies to channel directional asset management products. These activities leave paper trace to market players, and might be reflected in the banks' funding costs. We therefore propose our second hypothesis:

Hypothesis 2: *Banks with larger shadow loan exposure or more financial vulnerabilities face a higher funding cost.*

For this exercise, we use primary market data of negotiable certificates of deposit (NCDs). Banks in China have actively tapped into this funding source. As of 19 April 2021, the outstanding balance of NCDs is around CNY 12 trillion, with the average weekly issuance around CNY 370 billion over 2019–2020. As the key explanatory variables, we consider not only the shadow loan ratio but also the RNPL ratio and the NPL ratio.

We test Hypothesis 2 with the following three regressions:

$$\textit{NCD rate} = \beta_0 + \beta_1(\textit{shadow loan ratio}) + \beta_2(\textit{bank controls}) + \beta_3(\textit{bank-fixed effect}) + \varepsilon \quad (3)$$

$$\textit{NCD rate} = \beta_0 + \beta_1(\textit{RNPL ratio}) + \beta_2(\textit{bank controls}) + \beta_3(\textit{bank-fixed effect}) + \varepsilon \quad (4)$$

$$\textit{NCD rate} = \beta_0 + \beta_1(\textit{NPL ratio}) + \beta_2(\textit{bank controls}) + \beta_3(\textit{bank-fixed effect}) + \varepsilon \quad (5)$$

We expect that the shadow loan ratio in equation (3) has a positive and statistically significant relationship with banks' funding cost, as measured by the NCD issuance rate. In equation (4), we use the RNPL ratio derived from our reverse stress testing as the key independent variable, and expect it to be negatively and significantly related to the NCD issuance rate. Finally, in equation (5) where we use the NPL ratio instead of the RNPL ratio, we do not expect the statistically significant coefficient β_1 on the NPL ratio. This is because the use of shadow loans had masked

real problems and variations in the NPL ratio had been limited across banks within the same category until the breakout of Baoshang Bank failure.

The Baoshang Bank event on 24 May 2019, the first high-profile bank restructuring in two decades, shook market confidence in Chinese banks. If the financial market is efficient, the event shall have a stronger impact on weaker banks. As for Hypothesis 2, we consider the shadow loan ratio, the RNPL ratio and the NPL ratio as the key explanatory variables. Therefore, we propose our third hypothesis and test it with the following three regressions:

Hypothesis 3: *Less resilient banks experienced lower asset returns (equities and fixed income instruments) after the Baoshang Bank failure.*

$$\textit{Cumulative returns} = \beta_0 + \beta_1(\textit{shadow loan ratio}) + \beta_2(\textit{bank controls}) + \varepsilon \quad (6)$$

$$\textit{Cumulative returns} = \beta_0 + \beta_1(\textit{RNPL ratio}) + \beta_2(\textit{bank controls}) + \varepsilon \quad (7)$$

$$\textit{Cumulative returns} = \beta_0 + \beta_1(\textit{NPL ratio}) + \beta_2(\textit{bank controls}) + \varepsilon \quad (8)$$

We test Hypothesis 3 with secondary market data on returns on stocks and bonds issued by the banks. Shadow loan exposure should have a negative relationship with cumulative asset returns. The RNPL ratio should positively affect cumulative returns. Yet we do not expect any statistically significant results when we use the NPL ratio to measure a bank's resilience given the prevalent use of shadow loans to mask the problems.

We expect similar effects on the primary market activity. That is, the resilience of banks affects their NCD issuance amount during the Baoshang Bank event.

$$\textit{NCD issuance amount} = \beta_0 + \beta_1(\textit{shadow loan ratio}) + \beta_2(\textit{bank controls}) + \varepsilon \quad (9)$$

$$\textit{NCD issuance amount} = \beta_0 + \beta_1(\textit{RNPL ratio}) + \beta_2(\textit{bank controls}) + \varepsilon \quad (10)$$

$$\textit{NCD issuance amount} = \beta_0 + \beta_1(\textit{NPL ratio}) + \beta_2(\textit{bank controls}) + \varepsilon \quad (11)$$

However, we do not expect similar results on the NCD issuance rate due to the existence of selection bias. In particular, banks facing adverse issuance conditions, as reflected by higher NCD rates, are likely to suspend issuance during the interbank market turmoil following the Baoshang Bank event, and resort to other wholesale funding source.[11] Observed NCD issuance rates, therefore, tend to be dominated by healthier banks, hence less abnormal rates are expected.

[11] Interbank repo markets reportedly went through turmoil after the Baoshang Bank event in May 2019 (Galbraith and Zhou (2019)). However, we do not have access to transaction-level repo data to conduct a similar analysis as that on the NCD market.

4. Empirical results

4.1 Data

We construct a comprehensive half-yearly panel dataset for 51 listed Chinese banks (see Table A1 in the appendix for details) from H1 2016 to H1 2020 to test our hypotheses. We obtain financial statement data and key regulatory indicators of the listed banks from the WIND database. Shadow loan exposure is measured as the ratio of shadow loans to equity. We take into consideration the accounting standard changes [12] during the period of 2016–2020 when we calculate the shadow loan amount. Other data used in the tests include total assets, net profits, short-term debt, total deposits, and leverage measured as the ratio of equity over total assets, as well as regulatory monitoring indicators such as the NPL ratio, the CAR and the loan-to-deposit ratio. In addition, we collect detailed information on NCD issuance from WIND to measure the funding costs. For each bank in each half-year, we calculate the average NCD yield at issuance weighted by the NCD issuance amount. We then merge the weighted average NCD yield (NCD rate) with bank balance sheet information using bank names.

Table 2 provides summary statistics of half-yearly data from H1 2016 to H1 2020. The average value of the shadow loan ratio, defined as the ratio of shadow loans to total net worth of a bank, is 188.7%. The NPL ratio concentrates around 1.5% and the break-even NPL ratio (RNPL ratio) ranges from 0 to 15.6%. The mean of the CAR is around 13%. Finally, the NCD rate is 3.6% with the standard deviation lower than 1%.

Summary statistics — Table 2

	N	mean	sd	min	p25	p50	p75	max
Shadow loan ratio	428	188.67	149.91	0.45	73.56	155.68	274.89	661.09
NCD rate	448	3.56	0.84	1.59	2.99	3.26	4.49	5.26
CAR	449	13.16	1.44	7.47	12.09	13.03	14.00	18.08
NPL ratio	441	1.55	0.58	0.35	1.27	1.51	1.72	6.52
RNPL ratio	432	5.65	2.65	0.00	3.80	5.44	7.57	15.56
Leverage ratio	449	7.24	1.05	3.56	6.52	7.37	8.01	10.56
ROA	449	0.86	0.23	-0.54	0.73	0.86	0.99	1.84
Share_loan	443	45.81	8.70	23.52	39.26	46.50	53.04	62.46
Share_shortdebt	450	11.54	7.74	0.00	5.22	10.16	16.74	35.27
Share_deposit	449	63.94	8.96	43.35	57.26	63.06	70.18	91.37
Loan-to-deposit ratio	444	71.68	13.97	38.97	63.02	71.16	80.53	123.42
Log(total assets)	450	6.90	1.58	3.98	5.71	6.58	8.12	10.41

All variables are in per cent except log(total assets in billions of the Chinese yuen).

Sources: WIND; authors' calculations.

[12] We identify directional asset management plans (DAMPs) and trust beneficiary rights (TBRs) as the main forms of shadow loan. Since 2019, DAMPs and TBRs have been reported under the item of financial investment instead of under the old items such as available-for-sale financial assets, redemptory monetary capital for sale and investment receivables.

Table 3 reports the pairwise correlations among the main half-yearly variables. The shadow loan ratio exhibits a negative correlation with the leverage ratio and the CAR, while it has a positive correlation with funding costs measured by the NCD rate. Finally, the NCD rate is negatively correlated with the break-even NPL ratio (ie RNPL ratio) and positively but insignificantly correlated with the NPL ratio.

Pairwise correlations

Table 3

	Shadow loan ratio	NCD rate	CAR	NPL ratio	RNPL ratio	Leverage ratio	ROA	Share_ loan	Share _short debt	Share_ deposit	Loan-to-deposit ratio	Log (total assets)
Shadow loan ratio	1											
NCD rate	0.20*	1										
CAR	-0.50*	-0.17*	1									
NPL ratio	0.03	0.04	-0.29*	1								
RNPL ratio	-0.49*	-0.20*	0.69*	-0.25*	1							
Leverage ratio	-0.43*	-0.06	0.46*	0.16*	0.20*	1						
ROA	-0.04	-0.01	0.28*	-0.52*	0.20*	0.10*	1					
Share_loan	-0.73*	-0.18*	0.34*	0.20*	0.02	0.52*	-0.03	1				
Share_shortdebt	0.26*	-0.05	-0.31*	0.09	-0.35*	-0.20*	0.07	-0.10*	1			
Share_deposit	-0.45*	-0.11	0.31*	-0.12*	0.27*	0.14*	0.08	0.33*	-0.73*	1		
Loan-to-deposit ratio	-0.41*	-0.09	0.08	0.30*	-0.17*	0.37*	-0.14*	0.74*	0.39*	-0.35*	1	
Log(total assets)	-0.28*	-0.16*	0.12*	-0.04	-0.06	-0.10*	0.19*	0.32*	0.49*	-0.07	0.36*	1

* means statistical significance at the 10 percent level.

Sources: WIND; authors' calculations.

4.2 Regulatory arbitrage

To test our first hypothesis, we run fixed effect panel regressions for specifications (1) and (2) described in Section 3. Shadow loan exposure is measured as shadow loan-to-equity ratio of bank *i* in half year *t*. The CAR is the ratio of bank equity to risk-weighted assets of bank *i* in half year *t*. The leverage ratio is the equity-to-total assets ratio of bank *i* in half year *t*. We also consider the following set of standard bank characteristics as control variables: (i) ROA measured by net profits scaled by total assets; (ii) size measured by the logarithm of total assets; (iii) the ratio of NPLs to total loans; (iv) the share of short-term debt measured as the short-term debt scaled by total assets, where the short-term debt is the sum of short-term borrowing from the central bank, borrowing from other banks and deposits from other banks; (v) the share of deposits measured as total deposits scaled by total assets; and (vi) the loan-to-deposit ratio measured as total loans scaled by total deposits. To control bank-specific unobservable variables, we use bank fixed effects. Standard errors are clustered at the bank level to allow for correlation of error terms within banks.

Column (1) in Table 4 shows the regression results for equation (1) when we use the level of the shadow loan ratio as the dependent variable. Consistent with our conjecture, the contemporaneous CAR is not statistically significant, implying a successful regulatory arbitrage by banks. On the contrary, column (2) shows the

regression results for equation (2), which indicates a negative and statistically significant relationship between the leverage ratio and the shadow loan ratio. That is, the higher the leverage ratio, the lower the shadow loan ratio. This is consistent with our conjecture that capital constrained banks are more likely to engage in regulatory arbitrage. The magnitude is also economically significant: when the leverage ratio decreases by 1 percentage point, the shadow loan-to-equity ratio increases by 19 percentage points. Given that the average of the shadow loan-to-equity ratio is around 189%, a 1 percentage point decrease in the leverage ratio may contribute to around a 10% increase in the shadow loan ratio for an average bank.

Shadow loan exposure, the regulatory capital and leverage ratio Table 4

Dependent variable: Shadow loan ratio				
	Level		First difference	
	(1)	(2)	(3)	(4)
X=	CAR	Leverage ratio	CAR	Leverage ratio
X	-2.77	-12.60**	-9.11***	-15.31***
	(3.44)	(6.19)	(2.77)	(5.03)
ROA	-87.81***	-75.55***	-3.25	-4.28
	(23.5)	(22.72)	(16.24)	(12.43)
NPL ratio	-32.76***	-27.32**	-7.32	-8.54
	(10.54)	(11.00)	(7.06)	(8.28)
Log(total assets)	-165.56***	-155.51***	111.18	64.89
	(41.11)	(30.38)	(71.44)	(69.78)
Share_shortdebt	6.70***	6.40***	0.83	1.14
	(1.87)	(1.34)	(0.94)	(0.83)
Share_deposit	-1.92	-1.38	1.15	1.89
	(1.39)	(1.04)	(1.46)	(1.15)
Loan-to-deposit ratio	-3.63***	-3.27***	-0.36	-0.21
	(0.81)	(0.64)	(0.78)	(0.73)
Bank fixed effects	Yes	Yes	Yes	Yes
Observations	427	427	427	427
R-squared	0.912	0.913	0.30	0.29

Robust standard errors are in parentheses. ** and *** mean statistical significance at the 5 and 1 percent level, respectively.

For a robustness check, we consider an alternative specification by using the first difference of the shadow loan ratio as the dependent variable, as well as the first difference of all explanatory variables in columns (3) and (4). Notably, in column (4), the negative relationship between the leverage ratio and the shadow loan ratio remains both economically and statistically significant. In this specification, the coefficient on the CAR in column (3) is also statistically significant. A possible explanation is that regulatory tightening successfully forced banks to reduce shadow loans, while banks also stepped up their efforts to raise capital. So, the rise of the CAR coincided with the drop of the shadow loan ratio.

In order to see which type of banks drove the statistically significant coefficient on the CAR in the first-difference regression (Table 4, column (3)), we separately consider the four categories of banks. Table 5 shows that only city commercial banks

significantly increased the CAR and reduced the shadow loan ratio, while the other three types (state-owned, joint-stock and rural commercial) of banks did not show a significant relationship between the CAR and the shadow loan ratio.

We also conduct robustness checks with additional fixed effects: year-fixed effects and type-year fixed effects. Table A2 in the appendix shows that we obtain the qualitatively same results when we use alternative sets of fixed effects.

Shadow loan exposure and the regulatory capital ratio by bank type Table 5

Dependent variable: Shadow loan ratio				
	First difference			
Bank category	Rural commercial	City commercial	Joint-stock	State-owned
CAR	-2.45	-15.06***	-1.49	-3.74
	(1.934)	(4.121)	(2.623)	(2.749)
ROA	18.48	-1.59	39.56	5.24
	(25.65)	(16.50)	(52.07)	(6.210)
NPL ratio	-70.33	-12.26	42.89	-14.85
	(43.27)	(7.883)	(51.57)	(13.52)
Log(total assets)	-113.3	169.1**	47.98	24.78
	(96.58)	(72.93)	(102.1)	(33.44)
Share_shortdebt	-0.79	0.53	1.09	1.22
	(2.501)	(1.556)	(0.705)	(0.756)
Share_deposit	0.38	1.57	-2.57	-0.66
	(1.714)	(1.251)	(2.200)	(1.045)
Loan-to-deposit ratio	-0.01	0.51	-3.70**	-0.29
	(2.675)	(0.522)	(1.411)	(0.366)
Bank fixed effects	Yes	Yes	Yes	Yes
Observations	74	170	72	44
R-squared	0.205	0.339	0.484	0.638

Robust standard errors are in parentheses. ** and *** mean statistical significance at the 5 and 1 percent level, respectively.

Finally, as a robustness check, we consider the *RNPL* ratio which is the break-even NPL ratio where the regulatory minimum of the CAR is binding, as discussed in Section 2.3. While the CAR and the leverage ratio directly touch upon regulatory arbitrage, the RNPL ratio can capture hidden problems of banks which are seemingly healthy. Table A3 in the appendix shows that the RNPL ratio is strongly negatively correlated with the shadow loan ratio. This confirms that banks with lower RNPL ratios (that is, more vulnerable banks) tend to rely more on shadow loans. In the regressions reported in Table A3, we do not include the NPL ratio or the CAR as control variables because when we calculate the RNPL ratio, we already consider the NPL ratio and the CAR.

4.3 Market funding cost and bank risk from shadow loans

We explore whether the financial market is aware of banks' regulatory arbitrage. In particular, we look at the relationship between the shadow loan-to-equity ratio and banks' wholesale funding costs. Investors in the interbank market are wholesale

creditors to banks, the majority of which are banks and non-bank financial institutions. Banks usually collaborate with one or more financial institutions to structure their shadow loans. Such behaviour is highly visible in the market, so we conjecture that banks cannot avoid higher funding costs by hiding their loans as shadow loans. Capital strapped banks will have to pay a higher cost as investors demand compensation for the potential risk.

First, we test equation (3) in Hypothesis 2. The dependent variable is the *NCD rate,* the issuance amount-weighted average of the NCD rate at issuance across all NCDs issued by bank *i* in half year *t*. The positive and statistically significant relationship between the shadow loan ratio the NCD rate is confirmed as shown in column (1) of Table 6. However, the effects are not economically significant because a 1 percentage point increase in the shadow loan ratio is only associated with a 0.3 basis point increase in the NCD rate. Therefore, the inter-bank funding market reflects the heterogeneity in shadow activity exposure but to a limited extent, likely attributable to the prevalence of implicit guarantees on interbank markets. Using a first difference estimate, we obtain a similar result as shown in column (2) of Table 6.

The NCD rate and shadow loan exposure — Table 6

Dependent variable: NCD rate		
	Level	First difference
	(1)	(2)
Shadow loan ratio	0.003**	0.004**
	(0.0013)	(0.00156)
Log(total assets)	-0.143	-2.483*
	(0.587)	(1.242)
ROA	0.047	0.709***
	(0.295)	(0.160)
Share_shortdebt	-0.078***	-0.020
	(0.021)	(0.0122)
Share_deposit	-0.073***	-0.038**
	(0.0223)	(0.0185)
Loan-to-deposit ratio	0.003	0.008
	(0.009)	(0.0186)
Bank fixed effects	Yes	Yes
Observations	417	347
R-squared	0.722	0.113

Robust standard errors are in parentheses. *, ** and *** mean statistical significance at the 10, 5 and 1 percent level, respectively.

In order to see if the other more explicit and easy-to-obtain indicators for bank health and credit risk are priced in the funding market, we further test Hypothesis 2 using the specifications in equations (4) and (5). The tests serve as a horse race between the traditional NPL ratio and the break-even NPL ratio in terms of explaining the NCD rate.

Table 7 reports the regression results for equations (4) and (5). The RNPL ratio has a stronger relationship with the NCD rate than the NPL ratio: a 1 percentage point increase in the RNPL ratio is associated with a decrease in the NCD rate of around 18

to 20 basis points in different specifications, and their relationship is statistically significant. In contrast, the coefficient on the NPL ratio is only marginally statistically significant. This finding supports that the model-based break-even NPL ratio is reflected in the banks' wholesale funding costs, while the NPL ratio is not.

The NCD rate and the NPL and RNPL ratios

Table 7

Dependent variable: NCD rate				
	Level		First difference	
	(1)	(2)	(3)	(4)
X=	RNPL ratio	NPL ratio	RNPL ratio	NPL ratio
X	-0.207***	0.197*	-0.183***	-0.192*
	(0.0343)	(0.109)	(0.0312)	(0.109)
Log(total assets)	-0.677	-1.982***	-1.732	-1.472
	(0.544)	(0.433)	(1.204)	(1.388)
ROA	0.653*	0.494	0.989***	0.591***
	(0.366)	(0.299)	(0.212)	(0.210)
Share_shortdebt	-0.051***	-0.036**	-0.030**	-0.014
	(0.0148)	(0.0155)	(0.0116)	(0.0114)
Share_deposit	-0.070***	-0.066***	-0.059***	-0.027
	(0.00917)	(0.0116)	(0.0198)	(0.0230)
Loan-to-deposit ratio	-0.013	-0.015	-0.011	0.002
	(0.0120)	(0.0102)	(0.0195)	(0.0217)
Bank fixed effects	Yes	Yes	Yes	Yes
Observations	422	430	354	368
R-squared	0.352	0.251	0.174	0.069

Robust standard errors are in parentheses. *, ** and *** mean statistical significance at the 1, 5 and 10 percent level, respectively.

4.4 Market pricing of bank risk around the Baoshang Bank event

The announcement of Baoshang Bank restructuring in May 2019 and its eventual bankruptcy drew market attention to the credit risk and fragility of banks in China. Like a quasi-natural experiment of a real stress test, this event offers us a good opportunity to observe how the financial market prices bank risk, based on different measures of banks' vulnerabilities, namely shadow loan exposure, the RNPL ratio and the NPL ratio. We look at the following three securities markets for the listed banks: the equity market, Tier-2 capital bond market and NCD market.

We construct a cross-sectional dataset for an event study on the announcement of Baoshang Bank restructuring. It contains various types of cumulative equity returns, cumulative Tier-2 capital bond returns, and changes in the weighted average NCD rate around the event date. The data used to calculate these variables include daily equity prices, daily Tier-2 capital bond prices and the amount and rate at issuance for each NCD. For banks' Tier-2 capital bonds, we use the estimated prices provided by ChinaBond (China Central Depository & Clearing Co) when there is no actual transaction of bonds on a day. As a matter of fact, this is somewhat common because the Tier-2 capital bond market is relatively illiquid.

The restructuring of Baoshang Bank was announced after the market close on Friday 24 May 2019. We thus set the event date, ie date 0, as Monday 27 May 2019. We then look at cumulative equity returns and cumulative bond returns over a short period around the event date to gauge the immediate reaction from the stock and bond markets. We try different time windows (eg, [−1, 1], [0, 2], [−1, 5]) of trading days around date 0. Since there might have been information leakage on Baoshang Bank restructuring before the official announcement, we include one day before the event day in some windows.

Using the cross-sectional dataset, we test Hypothesis 3. Dependent variables include cumulative stock returns of bank i computed over the above test windows, cumulative Tier-2 capital bond returns of bank i computed over the above test windows, and the change in the NCD rate after the event date. Shadow loan exposure used in these tests is measured by the shadow loan ratio as of June 2019.[13] We estimate equations (6), (7) and (8) using OLS and heteroskedasticity-constant standard errors.

The results from the stock market are reported in Table 8. It shows that banks with larger shadow loan exposure or a lower RNPL ratio yielded significantly smaller cumulative stock returns after the announcement of Baoshang Bank restructuring, but that banks with a lower NPL ratio did not experience significantly smaller cumulative stock returns after the announcement.

We also conduct a few robustness checks. First, in order to avoid the results being driven by outliers, we classify the sample banks into two groups based on the sample median of shadow loan exposure. Then, we form a dummy variable of High Shadow Loan Ratio, which equals to 1 when a bank's shadow loan exposure is higher than the sample median and zero otherwise. Column (2) of Table 8 shows that the coefficient on the dummy variable is both economically and statistically significant. Second, we construct an alternative dependent variable of cumulative abnormal stock returns to remove the effect from the whole stock market trend. In particular, we use daily returns of the Shanghai stock index as market returns and apply the CAPM model to the banks' daily stock returns during 2019 and calculate the residual returns as abnormal returns. The results are all robust as shown in column (3).[14] Finally, the results reported in Table 8 are robust when we use the window of [0, 2] trading days as shown in Table A4 in the appendix.

Besides the shadow loan ratio, the model-based break-even NPL ratio from reverse stress testing (RNPL ratio) has significant explanatory power on stock returns (column (4)), while the NPL ratio does not explain the returns significantly (column (5)). A lower shadow loan ratio, which is usually accompanied by a higher RNPL ratio, is associated with higher cumulative returns in the stock market after the Baoshang Bank announcement. This suggests that the stock market priced in the vulnerabilities of banks related to shadow loans during the credit risk shock.

[13] We choose the June 2019 data instead of end-2018 data, as the former is closer to the event date. We also use the end-2018 observations of explanatory variables, and the results are robust.

[14] Due to space limit, we only report selected robustness results.

Cumulative stock returns around the Baoshang Bank event Table 8

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	CR[-1, 1]	CR[-1, 1]	CAR[-1, 1]	CR[-1, 1]	CR[-1, 1]
X=	Shadow loan ratio	High Shadow Loan Ratio dummy	Shadow loan ratio	RNPL ratio	NPL ratio
X	-0.011**	-2.200***	-0.006*	0.367**	-0.201
	(0.005)	(0.650)	(0.003)	(0.138)	(0.466)
Log(total assets)	0.730	0.599	0.786**	0.597	0.639
	(0.461)	(0.464)	(0.303)	(0.414)	(0.489)
ROA	-1.919	-1.199	-3.303**	-2.514	-0.803
	(1.845)	(1.449)	(1.506)	(1.754)	(2.294)
Share_shortdebt	-0.200	-0.197	-0.168	-0.194	-0.166
	(0.145)	(0.145)	(0.112)	(0.149)	(0.160)
Share_deposit	-0.254	-0.210	-0.188	-0.175	-0.174
	(0.176)	(0.162)	(0.134)	(0.152)	(0.166)
Loan-to-deposit ratio	-0.059	-0.036	-0.043	0.013	-0.012
	(0.053)	(0.045)	(0.039)	(0.041)	(0.044)
Observations	49	49	49	49	49
R-squared	0.302	0.298	0.282	0.293	0.256

CR stands for cumulative returns, and CAR for cumulative abnormal returns. See the text for how CAR is calculated. *, ** and *** mean statistical significance at the 10, 5 and 1 percent level, respectively.

The results using Tier-2 capital bonds are reported in Table 9. Since the bond market is less liquid than the equity market, a wider event window of sever days is appropriate to reflect a slower incorporation of information in market prices. Similar to the results in the stock market, the shadow loan ratio and the RNPL ratio significantly explain the seven-day cumulative bond returns around the event. The banks with larger shadow loan exposure or a lower RNPL ratio have smaller cumulative returns in the bond market. This is consistent with our conjecture that the capital market requires a higher return from banks with higher credit risk. The reaction from the bond market insignificantly relates to the differences in the NPL ratio, which consistently suggests that the RNPL ratio is a more robust measure of bank credit risk than the NPL ratio.

Finally, we conduct a similar event study for the NCD rate. Here, we calculate the weighted average NCD rate on or after the event date as well as that before the event date, and then calculate the change in the NCD rate by subtracting the pre-event NCD rate from the post-event NCD rate. Most banks issued NCDs every day around the event windows, but there are exceptions where some banks did not issue any NCD after the event. One reason can be self-selection: vulnerable banks cancelled NCD issuance after the event in anticipation of higher rates demanded by the market. To mitigate such abnormality for the event studies using NCD rates, we extend our time windows to three, five or ten days before and after the event date. We also look at the changes in the NCD issuance amount around the event date using an even wider window.

Cumulative bond returns around the Baoshang Bank event Table 9

Dependent Variable	CR[-1, 5]	CR[-1, 5]	CR[-1, 5]
X=	Shadow loan ratio	RNPL ratio	NPL ratio
X	-0.001***	0.020**	0.032
	(0.0003)	(0.00777)	(0.0415)
Log(total assets)	-0.021	-0.031	-0.026
	(0.0281)	(0.0327)	(0.0306)
ROA	-0.143	-0.137	0.071
	(0.119)	(0.126)	(0.169)
Share_shortdebt	0.014**	0.014**	0.014**
	(0.00623)	(0.00605)	(0.00611)
Share_deposit	0.008	0.013**	0.012*
	(0.00527)	(0.00634)	(0.00620)
Loan-to-deposit ratio	-0.004	0.001	-0.002
	(0.00340)	(0.00409)	(0.00366)
Observations	44	45	45
R-squared	0.321	0.246	0.179

CR stands for cumulative returns. *, ** and *** mean statistical significance at the 10, 5 and 1 percent level, respectively.

In contrast to the results on cumulative stock or bond returns, we find that changes in the NCD rate did not result in significant differences among banks with different shadow loan exposure or RNPL ratios around the event, even in wider time windows of up to 10 days before and after the event date (Table A5). This means that NCD pricing is not sensitive to the bank vulnerability indicators or the self-selection problem was serious.

Indeed, when we look at the change in the NCD issuance amount between the period of two (or three) months after the event and the period of two (or three) months before the event as per equations (9) to (11), we find that the banks with a higher shadow loan ratio, a higher NPL ratio and a lower RNPL ratio issued less NCDs after the event, suggesting a longer repercussion on the NCD market (Table 10).

5. Conclusion

This paper investigates how banks in China used shadow loans for regulatory arbitrage and whether the financial market saw through such use of shadow loans and the resulting vulnerabilities of the banks. We consider 51 listed Chinese banks, covering all large banks and most mid-sized banks from H1 2016 to H1 2020. We find evidence that banks chose to window dress its regulatory capital ratio by using shadow loans. We also find that banks with a higher shadow loan ratio or a lower breakeven non-performing loan (NPL) ratio (RNPL ratio) faced higher funding costs in the wholesale market as a risk premium on greater vulnerabilities. Finally, we show that the more vulnerable banks witnessed lower cumulative returns on both the equity market and the Tier-2 capital bond market and were able to issue less NCDs after the announcement of Baoshang Bank restructuring.

NCD issuance amount change around the Baoshang Bank event Table 10

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Difference in the NCD issuance amount between [0, d-1] and [-d, -1] periods					
X=	High Shadow Loan Ratio Dummy		RNPL ratio		NPL ratio	
d=	44 days	66 days	44 days	66 days	44 days	66 days
X	-0.359*	-0.457*	0.023	0.066	-0.407*	-0.518**
	(0.186)	(0.246)	(0.0439)	(0.0516)	(0.209)	(0.218)
Log(total assets)	0.037	0.179	0.025	0.159	0.042	0.183
	(0.137)	(0.180)	(0.140)	(0.180)	(0.117)	(0.152)
ROA	-0.023	-0.205	-0.053	-0.416	-0.668	-1.019*
	(0.361)	(0.369)	(0.444)	(0.450)	(0.540)	(0.518)
Share_shortdebt	-0.020	-0.038	-0.007	-0.024	-0.005	-0.020
	(0.0308)	(0.0325)	(0.0330)	(0.0322)	(0.0316)	(0.0302)
Share_deposit	0.018	0.003	0.035	0.024	0.037	0.027
	(0.0246)	(0.0266)	(0.0274)	(0.0264)	(0.0246)	(0.0231)
Loan-to-deposit ratio	-0.003	-0.001	0.008	0.015	0.010	0.016
	(0.0150)	(0.0164)	(0.0143)	(0.0159)	(0.0138)	(0.0147)
Observations	49	50	49	50	49	50
R-squared	0.264	0.293	0.245	0.287	0.288	0.329

* and ** mean statistical significance at the 10 and 5 percent level, respectively.

The paper's findings hold a number of policy implications for policy makers. First, it points to the importance of the regulatory framework to consider shadow banking activities to minimise regulatory arbitrage by banks and reduce the volatility of market reactions to negative shocks. Second, the results suggest that financial authorities consider not only traditional regulatory indicators such as the risk-weighted capital adequacy ratio and the NPL ratio but also other regulatory indicators such as the leverage ratio and the RNPL ratio. Third, the paper highlights the merit of conducting both traditional stress tests and reverse stress tests to identify the vulnerabilities of banks.

For future research, the paper's approaches can be extended to banks' exposure to various off-balance sheet shadow banking activities to assess the extent of regulatory arbitrage and how much the financial market prices in such shadow banking activities. Finally, in addition to financial stability implications of banks' relying on shadow loans, we can try to examine whether banks channel the shadow loans to more or less productive sectors to the extent that detailed data on the borrowers of the loans are available.

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Appendix

List of 51 banks in the sample — Table A1

Bank type	Bank name in English	Bank name in Chinese	Bank type	Bank name in English	Bank name in Chinese
State-owned	ABC	农业银行	City commercial	GSB	甘肃银行
State-owned	BoComm	交通银行	City commercial	Jinshang	晋商银行
State-owned	ICBC	工商银行	City commercial	Huishang	徽商银行
State-owned	PSBC	邮储银行	City commercial	JSB	江苏银行
State-owned	CCB	建设银行	City commercial	HZB	杭州银行
State-owned	BOC	中国银行	City commercial	Xian	西安银行
Joint-stock	Ping An	平安银行	City commercial	Nanjing	南京银行
Joint-stock	SPDB	浦发银行	City commercial	Beijing	北京银行
Joint-stock	Huaxia	华夏银行	City commercial	Shanghai	上海银行
Joint-stock	Minsheng	民生银行	City commercial	Changsha	长沙银行
Joint-stock	CMB	招商银行	City commercial	Chengdu	成都银行
Joint-stock	Industrial	兴业银行	City commercial	Guiyang	贵阳银行
Joint-stock	EverBright	光大银行	City commercial	HRB	哈尔滨银行
Joint-stock	CZB	浙商银行	City commercial	Jiujiang	九江银行
Joint-stock	CITIC	中信银行	City commercial	GZB	贵州银行
City commercial	Ningbo	宁波银行	Rural commercial	JYRCB	江阴银行
City commercial	ZZB	郑州银行	Rural commercial	Zhangjiagang	张家港行
City commercial	Qingdao	青岛银行	Rural commercial	Qingdao Rural	青农商行
City commercial	Suzhou	苏州银行	Rural commercial	Guangzhou RCB	广州农商银行
City commercial	JZB	锦州银行	Rural commercial	Wuxi Rural	无锡银行
City commercial	Zhongyuan	中原银行	Rural commercial	CQRCB	渝农商行
City commercial	Tianjin	天津银行	Rural commercial	CSRCB	常熟银行
City commercial	JXB	江西银行	Rural commercial	Zijin RCB	紫金银行
City commercial	Chongqing	重庆银行	Rural commercial	Suzhou RCB	苏农银行
City commercial	Luzhou	泸州银行	Rural commercial	JJRCB	九台农商银行
City commercial	Shengjing	盛京银行			

Shadow loan exposure, regulatory capital ratio and leverage ratio

Table A2

Dependent variable: Shadow loan ratio				
	Level			
X=	CAR	CAR	Leverage ratio	Leverage ratio
X	-4.53	-4.86	-19.76***	-19.09***
	(3.150)	(3.333)	(6.723)	(6.852)
ROA	-92.04***	-74.59***	-90.97***	-78.05***
	(20.64)	(18.48)	(20.32)	(18.58)
NPL	-25.33***	-22.58***	-27.81***	-26.54***
	(9.035)	(8.401)	(10.15)	(9.634)
Log(total assets)	-267.0***	-270.0***	-289.2***	-299.5***
	(67.57)	(72.70)	(65.15)	(68.96)
Share_shortdebt	7.48***	6.77***	7.18***	6.66***
	(1.642)	(1.644)	(1.588)	(1.538)
Share_deposit	-2.99	-2.73	-2.33	-2.09
	(1.883)	(1.907)	(1.822)	(1.868)
Loan-to-deposit ratio	-4.85***	-4.17***	-4.35***	-3.74***
	(0.895)	(0.816)	(0.916)	(0.831)
Observations	427	427	427	427
R-squared	0.918	0.925	0.921	0.927
Bank fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No
Bank type-year fixed effects	No	Yes	No	Yes
	First difference			
X=	CAR	CAR	Leverage ratio	Leverage ratio
X	-9.31***	-9.59***	-18.37***	-19.60***
	(2.497)	(2.679)	(5.349)	(6.047)
ROA	-0.98	0.46	-0.37	0.43
	(12.26)	(13.01)	(11.90)	(12.43)
NPL	-6.56	-6.06	-5.43	-5.97
	(7.066)	(7.058)	(6.882)	(6.737)
Log(total assets)	132.8**	118.9**	72.06	46.99
	(53.88)	(50.84)	(56.62)	(59.53)
Share_shortdebt	0.967	0.921	1.238	1.230
	(0.849)	(0.884)	(0.842)	(0.865)
Share_deposit	1.790	1.789	2.459**	2.448**
	(1.215)	(1.154)	(1.141)	(1.081)
Loan-to-deposit ratio	-0.368	-0.118	-0.223	0.0381
	(0.665)	(0.581)	(0.630)	(0.563)
Observations	360	360	360	360
R-squared	0.321	0.354	0.321	0.355
Bank fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No
Bank type-year fixed effects	No	Yes	No	Yes

Robust standard errors are in parentheses. ** and *** mean statistical significance at the 5 and 1 percent level, Respectively.

Shadow loan exposure and the RNPL ratio

Table A3

Dependent variable: Shadow loan ratio		
	Level	First difference
	(1)	(2)
RNPL ratio	-14.90***	-16.19***
	(2.623)	(1.834)
ROA	-1.245	27.66**
	(13.81)	(10.94)
Log(total assets)	-13.20	170.7***
	(39.69)	(45.89)
Share_shortdebt	5.693***	0.338
	(1.640)	(0.689)
Share_deposit	-2.941**	-0.281
	(1.249)	(0.930)
Loan-to-deposit ratio	-4.780***	-1.772***
	(0.650)	(0.558)
Bank fixed effects	Yes	Yes
Observations	427	360
R-squared	0.924	0.512

Sources: WIND; annual reports of banks; authors' calculations.

Accumulative stock returns of Baoshang Bank event, alternative test window

Table A4

Dependent Variable	CR[0, 2]	CR[0, 2]	CR[0, 2]	CR[0, 2]
X=	Shadow loan ratio	High Shadow Loan Ratio Dummy	RNPL ratio	NPL ratio
X	-0.0112**	-2.292***	0.363**	0.590
	(0.00422)	(0.606)	(0.136)	(0.437)
Log(total assets)	0.751	0.616	0.606	0.555
	(0.598)	(0.577)	(0.566)	(0.666)
ROA	-1.660	-0.932	-2.250	1.527
	(1.623)	(1.350)	(1.373)	(2.069)
Share_shortdebt	-0.195**	-0.193**	-0.187**	-0.161
	(0.0934)	(0.0890)	(0.0841)	(0.107)
Share_deposit	-0.135	-0.0911	-0.0540	-0.0432
	(0.0967)	(0.0904)	(0.0855)	(0.0994)
Loan-to-deposit ratio	-0.0208	0.00199	0.0508	0.0169
	(0.0517)	(0.0430)	(0.0477)	(0.0507)
Observations	49	49	49	49
R-squared	0.302	0.298	0.293	0.256

** and *** mean statistical significance at the 5 and 1 percent level, respectively.

Change in the NCD rate around the Baoshang Bank event

Table A5

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Difference in the average NCD rate between [0, d-1] and [-d, -1] periods					
X=	High Shadow Loan Ratio dummy		RNPL ratio		NPL ratio	
d=	3 days	10 days	3 days	10 days	3 days	10 days
X	0.0283	0.00822	-0.00678	-0.00355	-0.0564	-0.0415
	(0.0342)	(0.0331)	(0.0154)	(0.00685)	(0.0639)	(0.0353)
Log(total assets)	0.0317	0.0105	0.0352	0.0114	0.0290	0.0157
	(0.0334)	(0.0256)	(0.0421)	(0.0261)	(0.0334)	(0.0258)
ROA	-0.0682	0.00490	-0.0443	0.0225	-0.250	-0.109
	(0.0823)	(0.0779)	(0.0623)	(0.0708)	(0.257)	(0.129)
Share_shortdebt	-0.00545	-0.00388	-0.00569	-0.00398	-0.00551	-0.00390
	(0.00555)	(0.00468)	(0.00503)	(0.00471)	(0.00553)	(0.00406)
Share_deposit	-0.00503	-0.00716*	-0.00529	-0.00735*	-0.00734	-0.00797**
	(0.00757)	(0.00385)	(0.00616)	(0.00387)	(0.00882)	(0.00374)
Loan-to-deposit ratio	-0.00227	-0.00233	-0.00303	-0.00261	-0.00202	-0.00199
	(0.00340)	(0.00232)	(0.00377)	(0.00249)	(0.00311)	(0.00235)
Observations	29	43	29	44	29	44
R-squared	0.158	0.320	0.159	0.334	0.211	0.361

* and ** mean statistical significance at the 10 and 5 percent level, respectively.

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