The Implicit Non-guarantee in the Chinese Banking System*

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Abstract

Bank bailouts are systemic in China, having been extended to nearly all distressed banks, including those with no systemic importance. This paper investigates the consequences of regulators seizing control of Baoshang Bank, the country's first bank failure in two decades. Despite the numerous liquidity and credit provision measures immediately implemented by bank regulators, we find that the collapse of this city-level commercial bank significantly exacerbated funding conditions in the market for negotiable certificates of deposit (NCD), resulting in liquidity distress for other banks. Our empirical analysis demonstrates that the spillover of Baoshang's collapse is disproportionately concentrated in systemically unimportant (SU) banks, owing to diminished market confidence in government bailouts of SU banks, or *implicit non-guarantee*. We employ a difference-in-differences approach to show that the Baoshang event had a persistent and significant effect on SU banks' NCD issuance, increasing credit spreads by 21.9 bps and the likelihood of issuance failure by 6.3%. Our empirical framework further enables us to examine the impact of China's long-standing guarantee of SU banks, which we find impairs price efficiency, undermines market discipline, encourages excessive risk taking, and raises equity prices.

KEYWORDS: *Implicit guarantee*, *Bailout*, *Credit spread*, *Price efficiency*, *Market discipline*
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1 Introduction

Government guarantees are prevalent in China.[1] Since the failure of Hainan Development Bank in 1998, all distressed banks have been bailed out without going through the bankruptcy process, and all creditors have received full repayment. Thus, one fundamental issue in China's banking system is the well-anticipated systemic bailout, which will go beyond simply guaranteeing large banks deemed "too big to fail" (TBTF).[2] The collapse of a smaller regional lender, Baoshang Bank, announced on May 24, 2019, was the first time in the previous two decades that regulatory authorities deviated from this systemic bailout scheme. What are the consequences of this unexpected deviation from systemic bailouts? What are the impacts of the long-standing guarantee in the Chinese banking system? This paper sets out to answer these questions.

Our empirical analysis mainly focuses on the market for negotiable certificates of deposit (NCDs), one of the primary funding sources for banks seeking short-term financing in the interbank market. We first document that the Baoshang event resulted in some turmoil in the NCD market, despite regulators immediately intervening by injecting a substantial amount of liquidity into the market. Both the credit spreads on NCD issuance and the proportion of banks that failed on issuance increased significantly following this event (see Figure 1).[3] This pattern is persistent and continues even after the interbank rate (Shibor) began to decline significantly as a result of the central bank's liquidity injection.[4] In this way, the collapse of Baoshang, a very small city-level commercial bank, had a *spillover effect* on other banks, deteriorating their funding conditions. For instance, Bank of Jinzhou, another city-level commercial bank, experienced severe liquidity distress shortly after the event, thereby necessitating external supports and government intervention.

The main finding of this paper is that the spillover of the collapse of Baoshang is not a

[1]See, for example, Jin, Wang and Zhang (2020) and Geng and Pan (2021) for studies on guarantees extended to debts issued by state-owned enterprises, Liu, Lyu and Yu (2017) for the impacts of government guarantees offered to public bonds issued by local government financial vehicles (LGFVs), and Huang, Huang and Shao (2019) for banks' choices of extending guarantees to investors in wealth management products (WMPs).

[2]See Song and Xiong (2018) and Zhu (2016) for discussions on why implicit government guarantees pose a fundamental problem for the Chinese financial sector.

[3]This turmoil in the NCD market following the Baoshang event is also highlighted in the He (2020).

[4] The Shanghai Interbank Offered Rate (Shibor) is a daily reference rate based on the interest rates at which banks offer to lend unsecured funds to other banks in the Shanghai wholesale money market. They are calculated from rates quoted by the 18 banks with the highest credit ratings.

result of classic contagion mechanisms but rather a result of the diminished market confidence in government guarantees of systemically unimportant (SU) banks. We demonstrate that the adverse effect was concentrated in SU banks, whereas funding conditions for systemically important (SI) banks remained stable in the aftermath of the Baoshang collapse (see Figure 2).

Intuitively, after observing that the regulatory authorities are not going to continue the systemic bailout scheme and bail out all Baoshang creditors, the implied probability that future bailouts will be extended to another SU bank declines significantly. As a result, this implicit non-guarantee will be priced on SU banks' NCD issuance. Credit spreads on NCD issuance will then become more sensitive to the credit risks of issuing banks, thereby improving pricing efficiency. We construct a simple theoretical model to formalize this idea and to generate hypotheses for our formal empirical analysis.

To demonstrate that systemic importance is a critical factor in determining the spillover of Baoshang's failure, in our empirical study, we divide our samples into SU (*treatment* group) and SI (*control* group) banks. Our sample period is from October 1, 2018, to December 31, 2019, which presents roughly a two-quarter window before and after the event date of May 24, 2019. We employ the difference-in-differences (DiD) approach to examine how Baoshang's collapse changed credit spreads as well as the probability of successful issuance in the primary market of NCDs.

We begin our empirical analysis by testing the hypothesis that credit spreads will increase for SU banks, but not for SI banks, following the Baoshang event. Our baseline regression reveals that SU banks suffered a 21.9 basis points (bps) increase in the credit spreads on NCD issuance relative to SI banks after Baoshang's collapse. This estimator is reliable because the parallel trend assumption underlying DiD is validated. It is statistically significant and robust to incorporating additional controls, such as measures of banks' fundamentals. In addition, the estimated change of 21.9 bps in credit spreads is economically significant as the average credit spread for SU banks is 21.4 bps in the pre-event period. Furthermore, the observed change in the credit spread gap between SU and SI banks is quite persistent, lasting through the end of our sample period (see Figures 2 and 3).

To see how banks' funding conditions deteriorated after Baoshang's collapse, we then examine the *success ratio of issuance*—the ratio of the actual issuance size to issuing banks' planned issuance size—and the likelihood of *issuance success*—whether the actual issuance size is positive or zero—for SU and SI banks prior to and after Baoshang's collapse. Our

DiD regression demonstrates that, when compared with SI banks, SU banks' success ratio and likelihood of issuance success decreased by a greater magnitude of 10.3% and 6.3%, respectively.

We further examine mutual fund disclosures regarding their holdings of NCDs to gain insight into how institutional investors responded to Baoshang's collapse. It is noteworthy that mutual funds, particularly money market funds, are a primary funding source for the NCD market. Our DiD regression demonstrates that in the aftermath of Baoshang's collapse, fund managers significantly reduced their holdings of NCDs issued by SU banks in comparison to SI banks. For example, we find that the decline in the holding values of NCDs issued by SU banks is 27.0% greater than the decline in the holding values of NCDs issued by SI banks.

Taken together, our findings indicate that market reactions to the Baoshang event differ significantly between SU and SI banks. The observed pattern resembles a run on the NCDs issued by SU banks. To further establish that the spillover is caused by the diminished confidence in future government guarantees extended to SU banks, we conduct additional empirical analyses to rule out other alternative channels.

We first use measures of bank fundamentals (such as ROA, CAR, and NPL) as proxies for credit risks and show that Baoshang's collapse does not result in any significant change in the credit risk differential between SU and SI banks. As a result, the observed change in the credit spread gap between these two groups is unlikely to be driven by balance sheet contagion triggered by Baoshang's default on other banks. It is worth noting in this regard that the regulatory authorities channeled numerous funds from deposit insurance funds to ensure that the majority of Baoshang's creditors were fully repaid. The overall recovery rate for institutional investors with claims exceeding 50 million RMB is greater than 90%.[5] Therefore, the spillover caused by Baoshang's collapse is unlikely a result of the domino effect.

Likewise, as a result of the central bank's substantial liquidity injection following Baoshang's failure, the liquidity situation surrounding the Baoshang event is largely stable. As a result, a market-wide liquidity shortage is unlikely to be the cause of the observed data pattern. We further conduct a placebo test to rule out this possibility in a more rigorous way. The spread of rumors that regulators intend to incorporate off-balance-sheet wealth management products (WMPs) into the macroprudential assessment (MPA) framework's monitoring checklist immediately impaired a market-wide liquidity condi-

[5] See Section 2.3 for the details.

tion. However, unlike the pattern observed in the aftermath of the Baoshang event, the widening of the credit spread differential between SI and SU banks is only temporary following this event.

Furthermore, we provide additional evidence that (1) there has been no significant change in the size of SU banks' short-term borrowing and interbank exposures following the Baoshang event, in comparison to SI banks, and (2) any mechanism that amplifies banks' preexisting risks but is independent of the systemic importance factor (e.g., a change in investors' preferences and awareness of risks) cannot account for the observed change in credit spreads on NCD issuance.

Finally, we examine the credit spreads' sensitivity to bank risks on NCDs issued by SU and SI banks prior to and following the Baoshang event. As predicted by our theory, the implicit non-guarantee channel is characterized by an increase in the spread-to-risk sensitivity of SU banks, but not of SI banks. We use measures of bank fundamentals (e.g., ROA, CAR, NPL, and the liquidity ratio) for the bank's credit risks. The results from triple-difference regressions support this hypothesis of pricing efficiency. For example, our triple-difference regression demonstrates that a 1% difference in NPLs results in a significantly larger magnitude of increase in credit spreads for SU banks, 10.3 bps, relative to SI banks.

Therefore, our empirical analyses demonstrate that diminished confidence in the government guarantee of SU banks is most likely the mechanism underlying the Baoshang's collapse's spillover effect on other SU banks. This underscores an indirect contagion mechanism distinct from the classic ones, such as direct balance sheet contagion (Allen and Gale, 2000; Eisenberg and Noe, 2001) and indirect contagion caused by fire sales and common asset ownership (Duarte and Eisenbach, 2021; Greenwood, Landier and Thesmar, 2015).

Our evidence confirms that the Baoshang event eroded public confidence in future government bailouts, with a disproportionate impact on SU banks. As a result, a reasonable belief is that the change in market confidence is also associated with other financial market participants, such as equity investors, bank debt holders, and banks themselves. In this way, our empirical setting enables us to further examine the impacts of implicit non-guarantee on stock market responses, bank debt holders' monitoring, and banks' risk-taking behavior.

The empirical findings of an event study indicate that equity investors' responses are consistent with those of NCD investors. Within a 60-day event window following the collapse of Baoshang Bank, the cumulative abnormal returns of listed SU banks are negative, while those of listed SI banks are positive. This finding is consistent with the findings in many previous studies on other banking systems that implicit guarantees increase banks' equity prices (see, among others, O'hara and Shaw (1990), Atkeson et al. (2019) and Gandhi, Lustig and Plazzi (2020)).[6]

We further show that, in the aftermath of the Baoshang event, SU banks are associated with significantly higher deposit-to-asset ratios and significantly lower risk-sensitive debt-to-asset ratios, as compared with SI banks. Moreover, risk-taking behavior, as measured by the volatility of ROA and its variants, is significantly reduced following the event for SU banks, in comparison to SI banks. These results confirm that anticipation of government bailouts indeed promotes excessive risk taking and jeopardizes market discipline for SU banks.

The contribution of this paper is threefold. First, we document the consequences of an unexpected policy shift in China's systemic bailout scheme. We present extensive evidence demonstrating how investors in NCDs, equity market participants, and banks reacted to this observation. On the one hand, similar to the approaches in Cutura (2021) and Gropp, Gruendl and Guettler (2014), we rely on an event — the incomplete bailout in the Baoshang case — to examine the impact of an change in the perception of government guarantees. In contrast to these papers, our event involves only a minor deviation from a systemic bailout, as the government continued to bail out the majority of Baoshang's creditors,[7] and there was no explicit policy change in government guarantee, even for systemically unimportant banks. Our study demonstrates that a minor loosening of the systemic bailout scheme results in market turmoil for NCDs and liquidity distress,[8] confirming the strong market anticipation of the government bailout in China.[9]

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[6]It is worth noting that our evidence demonstrates that the equity premium of guarantee is associated with listed SU banks, which should not be interpreted as a "size premium" or "TBTF premium." See also Minton, Stulz and Taboada (2019) for evidence that large banks are not valued more highly than other firms.

[7]It is worth noting that by declining to bail out all of Baoshang's creditors, the regulatory authorities may have a stronger incentive to provide guarantees and assistance to other distressed banks. This is consistent with our observations during the market turmoil following Baoshang's collapse, as well as with the theoretical prediction in Dovis, Kirpalani et al. (2018).

[8]Focusing on the CD market in the US, Ellis and Flannery (1992) find that CD rates paid by banks are sensitive to the perceived credit risks. Another potential advantage of our empirical setting is that the NCD issuance data enable us to examine the difference between actual and planned issuance sizes, which provides extra information about our event's impact on the funding conditions of affected banks.

[9]In this way, our study is also related to Kelly, Lustig and Van Nieuwerburgh (2016). The authors use

On the other hand, we find that the Baoshang event has a disproportionate impact on systemically unimportant banks, raising credit spreads and increasing the likelihood of issuance failure, while systemically significant banks' funding conditions remain stable. This distinguishes our work from the existing literature on TBTF, which focuses primarily on the implied expectation of guarantee on *systemically important* banks and its effects on these banks' funding conditions. For example, see Acharya, Anginer and Warburton (2016) and Berndt, Duffie and Zhu (2021) for how the collapse of Lehman Brothers affected the implied expectation of TBTF.[10]

The second contribution of our study highlights a contagion mechanism through which the failure of a small bank can spread to a large number of other banks. This mechanism of contagion is triggered by diminished confidence in a future government bailout and is independent of any material connection between the failing bank and the affected banks. Interestingly, as evidenced by the Baoshang case, conventional interventions such as liquidity injections may be ineffective at mitigating this spillover effect. According to Farhi and Tirole (2012) and Bianchi (2016), a systemic and size-independent bailout scheme can be desirable from an *ex ante* perspective. However, we demonstrate empirically that the *ex post* cost of exiting such a systemic bailout (even a minor deviation) can be significant and, thus, should not be ignored in the optimal design of the bailout scheme.

Finally, our study sheds light on the understanding of the impact of long-standing guarantees on the Chinese banking sector. There is a large literature examining the relationship between government bailouts (and the expectation of them) and bank risk-taking behavior, but no unified answer exists. On the one hand, the safety net contributes to moral hazard (Dam and Koetter, 2012), while on the other hand, it increases bank charter values, discouraging risk-taking (Hakenes and Schnabel, 2010; Keeley, 1990).[11]However, little research has been conducted on the effect of China's systemic bank bailouts on bank's risk-taking behavior, in particular for small banks. The difficulty in addressing this question stems from the fact that in China, there is little variation in the government guarantee, and even if there were, changes in *implicit* guarantees are difficult to observe

option data to examine the systemic guarantee provided to the financial sector during the global financial crisis.

[10]The impacts of TBTF on banks' borrowing costs have also been analyzed for European banks; see, e.g., Lindstrom and Osborne (2020) and Neuberg et al. (2018). See Buch, Dominguez-Cardoza and Völpel (2021) for a recent survey on this topic.

[11]See Cordella and Yeyati (2003) for a theoretical model that highlights this trade-off.

or quantify.[12] However, our empirical approach enables us to rule out alternative mechanisms and identify a shift in market beliefs about future government guarantees. In this way, our study provides an answer to this question, but only for the impacts of government guarantees on systemically unimportant banks. We find convincing evidence that systemic government guarantees do, in fact, account for SU banks' excessive risk taking and weakened market discipline.[13]

Outline The remainder of this paper is structured as follows. Section 2 provides background information on the Chinese banking system, the Baoshang event, and the NCD market, as well as a brief discussion of the subsequent market reactions to the Baoshang event. We develop a simple model and hypotheses in Section 3 to guide our formal empirical analysis. Section 4 describes the data and provides summary statistics. Section 5 presents the empirical findings on how the Baoshang event differs in its impact on NCDs issued by SU and SI banks. Section 6 discusses possible alternative explanations for the observed data pattern and further establishes that Baoshang's collapse, through the channel of implicit non-guarantee, increases the sensitivity of credit spreads to banks' credit risks. The effects of the implicit guarantee on the equity market, banks' risk taking, and market discipline are examined in Section 7. Section 8 discusses the robustness of our findings, and Section 9 concludes.

2 Institutional Backgrounds

2.1 Commercial Banks in China

In China, deposit-taking financial institutions, or *commercial banks*, are classified as follows: state-owned commercial banks, joint-stock commercial banks, city-level commercial banks, rural commercial banks, and rural credit cooperatives. The six largest commercial banks in China — the Industrial and Commercial Bank of China, the China Construction Bank, the Bank of China, the Agricultural Bank of China, the Bank of Commu-

[12] For example, Gormley, Johnson and Rhee (2015) provide evidence that even with a promised no-bailout scheme, beliefs of TBTF were not eliminated because investors believed that this policy was not time consistent. In addition, many studies (e.g., Berndt, Duffie and Zhu (2021)) adopt a structural approach to estimate the implied probability of government guarantee from the market data.

[13] This may account for SU banks' higher non-performing loan (NPL) rate, on average, as compared to SI banks. See Section 4 for details.

nications, and the Postal Savings Bank of China — are all state owned and account for approximately 39.2% of the Chinese banking system's assets by the end of 2020. Twelve medium-sized joint-stock commercial banks account for approximately 18.2% of the Chinese banking system's assets and deposits, while 133 small city commercial banks account for approximately 13.1%.[14] In addition, China has over 1,500 rural commercial banks and credit unions with small assets and liabilities.

Banking regulatory authorities in China, including the People's Bank of China (PBOC) and China Banking and Insurance Regulatory Commission (CBIRC), retain considerable influence over banks' lending and deposit-taking activities because of their majority ownership of the largest Chinese banks, in contrast to banking systems that are predominantly privately owned and controlled. For instance, the PBOC establishes benchmark interest rates on bank deposits and loans of various maturities, implements quarterly quotas on bank loans, and sets explicit limits on the proportion of bank loans that can be extended to certain industries (e.g., the real estate sector). As such, bank lending decisions frequently reflect government policy priorities, favoring state-owned enterprises and government infrastructure projects disproportionately.

Implicit Government Guarantees More remarkable is that the government has been bailing out the creditors of all distressed banks since 1998, when Hainan Development Bank declared bankruptcy. Given that small community banks and credit unions were also rescued, the underlying reason behind government bailouts should go beyond avoiding systemic financial crises. Rather, the rationale could be linked to these banks' previously assumed obligations to cooperate with central or local government policies, as well as to ex post social harmony and stability.

Systemically Important Banks On October 15, 2021, the PBOC and CBIRC released an official list of systemically important banks (see Table A1 in Appendix A), which includes all six state-owned banks, nine joint-stock commercial banks, and four city banks. SI banks operate on a national scale and typically have a much larger asset base than SU banks. At the aggregate level, SI (SU) banks account for 77% (23%) of total Chinese banking assets. In Panel B of Table 1, we compare SI and SU banks in detail. The regulatory authorities apply more stringent capital requirements to systemically important banks.

[14]If not specified otherwise, the data in this section come from the same sources as the data used in our empirical analysis, which is discussed in Section 4.1.

2.2 The Market of Negotiable Certificates of Deposit (NCDs)

NCDs are certificates of deposit with a minimum face value and a fixed term. On December 9, 2013, China established the NCD market. In this market, NCDs must be at least 50 million RMB in size and are only available to financial institutions in the interbank market. NCDs are short term in nature, with a maturity of one month to one year. The primary purpose of introducing NCDs was to improve the transparency of the interbank market and to liberalize the interest rate, mainly the deposit and lending rates of commercial banks.

NCDs are issued in a manner similar to bonds. The issuing bank (seller) first specifies the planned issuance size and price of the issuance (interest rate). Following that, investors (buyers) specify the size of the security they wish to acquire at the specified price. NCD sales begin at 9 a.m. and continue until 5:15 p.m. on the same day. While the sale will automatically end if the total purchase amount exceeds the planned amount. Thus, the *actual issuance size*, or total purchase amount, is either less than or equal to the planned issuance size. If the actual size of the issuance is zero, we say the issuance *fails*.

The Shanghai Interbank Offered Rate (Shibor) serves as a reference rate for NCDs of equivalent maturity.[15] In addition, NCDs are traded on the secondary market and are eligible for use as collateral in repurchase transactions.

The NCD market has grown at a tremendous speed since its inception. NCD issuance exceeded 20 trillion RMB in 2017, and outstanding NCDs account for approximately 5% of total liability in China's banking sector. To understand the boom in the NCD market, it is necessary to highlight the critical distinctions between NCDs and other forms of financing. In contrast to deposits, NCDs do not have a reserve requirement. Moreover, prior to August 2017, NCDs were not treated as other types of interbank liabilities, which are limited to one-third of a bank's total liability under regulation. Furthermore, unlike bond issuance, which requires approval from both the PBOC and the CBIRC, commercial banks have more flexibility when it comes to the timing and size of NCD issuance.

The dominant players in the NCD market are joint-stock and city-level commercial banks, which are at a disadvantage in competing with large banks for household and corporate deposits. These banks rely heavily on the issuance of NCDs to grow their balance sheets and manage their liquidity positions. By the end of 2020, joint-stock commercial bank held 40.80% of all outstanding NCDs, while city-level commercial banks held 32%.

[15] See footnote 4 for how the Shibor rate is determined. Also note that there are eight Shibor rates, with maturities ranging from overnight to a year.

The major NCD investors include mutual funds (including money market mutual funds, bond funds, and hybrid funds), state-owned banks, and rural banks and credit unions. By the end of 2020, mutual funds in total funded 49.28% of the outstanding NCDs; that ratio is 18.39% for rural banks and credit unions and 8.89% for state-owned banks.

2.3 The Collapse of Baoshang Bank

Baoshang Bank was established in the Inner Mongolia Autonomous Region in December 1998. On May 24, 2019, the PBOC and CBIRC jointly announced that CBIRC had decided to take over Baoshang Bank in response to serious credit risks. During the takeover, China Bank of Construction was tasked with managing the operation of Baoshang's branches. Prior to the takeover, Baoshang's assets totaled 550 billion RMB, or approximately 0.25% of total Chinese commercial banking assets.[16] In this sense, Baoshang Bank is a small city-level commercial bank in China.

The Causes of Baoshang's Collapse The inspection by regulators revealed a 220 billion RMB capital shortfall in the bank's assets, posing a significant credit risk to the bank's creditors. Baoshang's collapse was not a result of a macroeconomic recession or market-wide liquidity distress. Rather, it was an idiosyncratic event brought about by the controlling shareholders' misconduct and corporate governance failure. Tomorrow Holding, Baoshang's largest shareholder, is a private conglomerate that owns 89% of the bank. Tomorrow Holding was reported to have illegally borrowed 150 billion RMB from Baoshang between 2005 and 2019 via 209 shell companies in the form of 347 loans that all ended up becoming non-performing.[17]

Regulatory Authorities' Subsequent Responses Shortly after the takeover, CBIRC assured Baoshang creditors during a Q&A session that all claims under 50 million RMB would be fully repaid, including principal and interest. Creditors with claims exceeding

[16] These data are provided by the PBOC; see PBOC (2021) for details.

[17] For details, see Zhang Yuzhe, Wu Hongyuran, and Liu Jiefei, "Central Bank Urges Calm After Taking Control of Baoshang Bank," Caixin Global, June 3, 2019, https://www.caixinglobal.com/2019-06-03/central-bank-urges-calm-after-taking-control-of-baoshang-bank-101423061.html and Wu Hongyuran, Peng Qinqin, and Denise Jia, "Chinese Government Takes Over Bank Linked to Fallen Tycoon," Caixin Global, May 25, 2019, https://www.caixinglobal.com/2019-05-25/chinese-government-takes-over-fallen-tycoons-bank-101419763.html.

50 million RMB, on the other hand, may incur losses, with a recovery rate ranging from 70% to 90% depending on the size of the claim. This event marked the first time in two decades that the government refrained from bailing out all bank creditors.

The regulatory authorities took a number of steps to reestablish market confidence and avert a domino effect. The PBOC injected a net amount of 150 billion RMB via open-market operations on May 26 and 27. On June 6, the PBOC expanded its lending to financial institutions by 500 billion RMB through its medium-term lending facility (MLF).[18]

Further, on June 9, 2019, the PBOC stated that it had no plans to take over additional banks and would instead use a variety of monetary policy tools to stabilize money markets and boost banking system liquidity.[19] In addition, to ensure the continued normal operation of Baoshang, the regulatory authorities provided guarantees to Baoshang's new NCD issuance after the takeover. To avoid further amplification of the Baoshang shock, such explicit guarantees later were extended to another distressed bank, Bank of Jinzhou, which we will soon discuss.

Resolution and Restructuring On August 6, 2020, Baoshang Bank filed for bankruptcy. According to PBOC (2021), the PBOC and CBIRC provided capital from the national deposit insurance fund to ensure a full repayment for personal deposits and the vast majority of institutional creditors. The support from the deposit insurance fund totaled 184.4 billion RMB, among which 34.4 billion RMB was provided to Huishang Bank to help cover acquisition costs. Additionally, a new bank, Mengshang Bank, was established to acquire the assets and liabilities of Baoshang, in collaboration with Huishang Bank, the Inner Mongolia local government, and other state investors. The resolution was settled on February 7, 2021. In the end, losses occurred only to institutional creditors with over 50 million claims, and the overall coverage ratio was greater than 90%.

[18] For details, see the Bloomberg report: https://www.bloomberg.com/news/articles/2019-05-28/pboc-adds-liquidity-as-baoshang-seizure-ratchets-up-bank-stress, and the Reuters report: Winni Zhou and Andrew Galbraith, "China Central Bank Steps Up Liquidity Support for More Banks after Baoshang Takeover," Reuters, June 5, 2019, https://www.reuters.com/article/us-china-economy-mlf-idUSKCN1T706E.

[19] For details, see Winni Zhou and Andrew Galbraith, "China Central Bank Steps Up Liquidity Support for More Banks after Baoshang Takeover," Reuters, June 5, 2019, https://www.reuters.com/article/us-china-economy-mlf-idUSKCN1T706E.

Bank of Jinzhou It is worth noting that a Hong Kong-listed city-level commercial bank, Bank of Jinzhou, experienced severe liquidity difficulties shortly after Baoshang's collapse. Between May 25 and June 9, 16 days after the announcement of Baoshang's collapse, Bank of Jinzhou successfully issued only two NCDs, raising 0.22 billion RMB in total (against a planned issuance of 1.5 billion).[20] As a result, on June 10, 2019, the regulatory authorities issued temporary guarantees for Bank of Jinzhou's NCD issuance, which were later revoked on July 30, 2019.[21] Moreover, bank regulators and local governments oversaw Bank of Jinzhou's subsequent market-oriented restructuring of the Bank of Jinzhou. On July 28, 2019, the Industrial and Commercial Bank of China (ICBC) acquired 10.82% of Jinzhou's stock and became the controlling shareholder.[22]

2.4 Market Responses after the Baoshang Event

It was unexpected that the regulatory authorities would allow Baoshang to go bankrupt and some bank creditors to suffer losses without government bailouts, given that this event had never occurred in the previous two decades.[23]

The market reaction confirms this. We first show that the overall liquidity condition remained stable because of massive liquidity injections by bank regulators. As illustrated in Panel A of Figure 1, the three-month Shibor interest rate increased by 4.5 bps in the 15 days following the Baoshang event and then began to decline significantly after June 17, 2019.

Despite the stable market liquidity, the Baoshang event has had a significant adverse impact on the NCD market's funding conditions. Panel A of Figure 1 shows that the average credit spreads on NCD issuance for all banks increased from 18.7 bps on May 24

[20] In comparison, prior to the Baoshang event, Jinzhou successfully issued 18 NCDs in 16 days (from May 8 to May 23, 2019), raising 5.73 billion RMB in total.

[21] See the Moody's article reported on S&P Global: Regina Liezl Gambe, "Moody's: PBOC's Credit Enhancement for Bank of Jinzhou Is Credit Positive," S&P Global, June 17, 2019, https://www.spglobal.com/marketintelligence/en/news-insights/trending/b_4vl94ulmaph-fwzyzw_q2 for details.

[22] Similar to the case of Bank of Jinzhou, Hengfeng Bank, a joint-stock commercial bank, encountered similar difficulties and was later restructured in 2019. See PBOC (2021) for details.

[23] It is important to note that the government indeed bailed out the majority of Baoshang's creditors. It was reported that "[w]ithout the intervention of public funds, the average repayment rate of creditors would be less than 60% in theory." For details, see "Baoshang Bank Set to Go Bankrupt, PBOC Says Senior Execs Will Be Held Accountable," China Banking News, August 7, 2020, https://www.chinabankingnews.com/2020/08/07/baoshang-bank-set-to-go-bankrupt-pboc-says-senior-execs-will-be-held-accountable/.

to 35.2 bps on June 24, marking an increase of 88.2%. Apart from the soaring funding costs, banks encountered significant challenges in raising money through NCD issuance. Panel B of Figure 1 suggests that, within 5 trading days, the proportion of *NCD issuance* that failed to raise any money jumped from 6.3% on May 23 to 45.2% on June 3, corresponding to an increase of 617.5%. In addition, the proportion of *banks* that could not obtain financing from the NCD issuance increased from 7.5% on May 23 to 43.9% on June 3, which is equivalent to a 485.3% increase. As illustrated in Figure 1, the effects of Baoshang's collapse on credit spreads and the likelihood of issuance failure were quite persistent, lasting at least three months.This deterioration in funding conditions in the NCD market created severe liquidity problems for other banks (e.g., Bank of Jinzhou).

[Figure 1 About Here]

To summarize, following the Baoshang event, the government ended up providing massive liquidity support and various guarantees to the banking system, as well as bailing out the majority of Baoshang's creditors. This step preserved the liquidity condition and averted a severe fundamental contagion caused by Baoshang's default. However, this shock exacerbated funding conditions in the NCD market, a primary source of funding for banks to meet their liquidity needs and expand their balance sheet. More specifically, credit spreads have increased dramatically and persistently, and many banks have been unable to obtain funding through NCD issuance. In Section 5, we will conduct a more in-depth examination of the Baoshang event, focusing on the significance and persistence of changes in credit spreads and the issuance failure following the Baoshang shock.

3 Theory and Hypotheses

In this section, we construct a simple model to demonstrate how the failure of an SU bank can change the market perceptions of implicit government guarantees. In this way, it can adjust market pricing for debt issued by other SU banks, even in the absence of any fundamental risk spillover. This theoretical exercise will generate testable hypotheses to guide our empirical analysis.

3.1 A Simple Model

We consider a "normal" episode of time t when there is no economic recession or systemic financial distress. At this time, bank distress, if it occurs, is likely to be an idiosyncratic event. Any bank i is either an SI bank ($s = I$) or an SU bank ($s = U$). The ex post realization of $g^s_{i,t}$ governs the guarantee extended to any bank i in category s at time t. More specifically, $g^s_{i,t} = 1$ if the guarantee is provided; otherwise, $g^s_{i,t} = 0$.

The realization of $g^s_{i,t}$ is determined by a time-invariant (stochastic) variable of government guarantee g that is universally applied to all banks,[24] and idiosyncratic factors $\alpha^s_{i,t}$ and $\beta^s_{i,t}$ as follows:

$$g^s_{i,t} = g + \mathbb{1}\{g = 0\}\alpha^s_{i,t} - \mathbb{1}\{g = 1\}\beta^s_{i,t}. \tag{1}$$

As discussed, government bailouts in China were previously extended to almost all distressed financial institutions, not just to systemically important banks. If the government guarantee will be extended universally to all banks (unless there are some bank-specific reasons), then $g = 1$; and $g = 0$ means the opposite — unless there are bank-specific reasons, no bank will be bailed out.

The terms $\alpha^s_{i,t} \in \{0, 1\}$ and $\beta^s_{i,t} \in \{0, 1\}$ capture the idiosyncratic characteristics of bank i that may make it unique. More precisely, even if the guarantee is not universally provided (i.e., $g = 0$), it will be provided to bank i in category s; that is, $\alpha^s_{i,t} = 1$ and, thus, $g^s_{i,t} = 1$. This can occur because this bank is systemically important (i.e., $\alpha^I_{i,t} = 1$), or it can occur because the failure of an SU bank jeopardizes regional financial or social stability. Similarly, even if the guarantee is universally provided to banks (i.e., $g = 1$), it is possible that it is not provided to this bank if $\beta^s_{i,t} = 1$, for reasons related to money laundering, mortgage fraud, and other illegal activities, for example. We assume that these idiosyncratic factors are independent across time t and across different banks and thus cannot be learned from prior experiences.

We denote the public belief about g at time t as $p_t \equiv \mathbb{P}(g = 1|h_t)$, in which $h_t \in \mathcal{H}_t$ stands for the history of observations prior to time t. For SI banks, because they are "too big to fail" or "too connected to fail," $\alpha^I_{i,t} = 1$ and $\beta^I_{i,t} = 0$. Therefore, SI banks are always guaranteed (i.e., $g^I_{i,t} = 1$) regardless of g.

The focus of our theoretical analysis is SU banks. For any SU bank i, we assume that the market holds the common belief that $\mathbb{P}(\alpha^U_{i,t} = 1) = \eta_i$ and $\mathbb{P}(\beta^U_{i,t} = 1) = \tau_i$ at any time t.[25] Given that it is unlikely for any SU bank to be a unique one, the values of η_i and τ_i

[24] We believe that the universal government guarantee remains unchanged over a relatively long period of time (e.g., the duration of a government or political system). Obviously, we cannot have only time-varying variables with no persistence. In that case, the market gains no information from previous observations.

[25] More precisely, it is assumed that $\alpha^U_{i,t}$ is independent of $\beta^U_{i,t}$, $\alpha^U_{i,t'}$ and $\beta^U_{i,t'}$ for $t' \neq t$, as well as the idiosyncratic factors of other bank $j \neq i$ (i.e., $\alpha^U_{j,t}$ and $\beta^U_{j,t}$ for all t).

are assumed to be very small, satisfying $\eta_i \in (0, 0.5)$ and $\tau_i \in (0, 0.5)$.

Based on these assumptions, the perceived probability that the government guarantee will be extended to any SU bank i at time t is

$$\begin{aligned} p_{i,t}^U \equiv & \mathbb{P}(g_{i,t}^U = 1|h_t) = \mathbb{E}(g_{i,t}^U|h_t) = \mathbb{P}(g = 1|h_t) \left[1 - \mathbb{E}(\beta_{i,t}^U)\right] + \mathbb{P}(g = 0|h_t)\mathbb{E}(\alpha_{i,t}^U) \\ = & p_t(1 - \tau_i - \eta_i) + \eta_i. \end{aligned} \tag{2}$$

Since $\tau_i + \eta_i \in (0, 1)$ by assumption, the perceived probability of an implicit guarantee is increasing in p_t, or the expected universal guarantee based on time-t information.

Implicit Non-guarantee

Now, suppose the market observes $g_{j,t}^U = 0$ at time t; that is, the government guarantee was *not* extended to a distressed SU bank j at time t. Assuming that all market participants are Bayesian, they update their beliefs about the universal guarantee parameter g at $t + 1$ as follows:

$$\begin{aligned} p_{t+1}(g_{j,t}^U = 0, p_t) \equiv & \mathbb{P}(g = 1|g_{j,t}^U = 0, h_t) = \frac{\mathbb{P}(g_{j,t}^U = 0|g = 1, h_t)\mathbb{P}(g = 1|h_t)}{\sum_{g=0,1} \mathbb{P}(g_{j,t}^U = 0|g, h_t)\mathbb{P}(g|h_t)} \\ = & \frac{p_t}{p_t + (1 - p_t)\frac{1-\eta_j}{\tau_j}}. \end{aligned}$$

Because $\frac{1-\eta_j}{\tau_j} > 1$, the market is less optimistic about a universal guarantee after observing a failure of an SU bank; that is, $p_{t+1} < p_t$ for any $p_t \in (0, 1)$.

In the opposite scenario, the market observes that a distressed bank j is bailed out by the government at time t (i.e., $g_{j,t}^U = 1$). Then,

$$\begin{aligned} p_{t+1}(g_{j,t}^U = 1, p_t) \equiv & \mathbb{P}(g = 1|g_{j,t}^U = 1, h_t) = \frac{\mathbb{P}(g_{j,t}^U = 1|g = 1, h_t)\mathbb{P}(g = 1|h_t)}{\sum_{g=0,1} \mathbb{P}(g_{j,t}^U = 1|g, h_t)\mathbb{P}(g|h_t)} \\ = & \frac{p_t}{p_t + (1 - p_t)\frac{\eta_j}{1-\tau_j}} \end{aligned}$$

Clearly, such an observation boosts the confidence of the universal government guarantee because $\frac{\eta_j}{1-\tau_j} < 1$. Therefore, we have

$$p_{t+1}(g_{j,t}^U = 1, p_t) > p_t > p_{t+1}(g_{j,t}^U = 0, p_t).$$

Given that the perceived probability of a government guarantee that will be extended to any SU bank i at time $t+1$, $\mathbb{P}(g^U_{i,t+1} = 1)$, increases with p_{t+1} (see (2)), a time-t observation of government bailout (no bailout) extended to bank j increases (decreases) this perceived probability.

Proposition 1 (Implicit Non-guarantee and Bank Failure)**.** *For any SU bank i, any time t, and any history h_t, the perceived probability of a government guarantee decreases (increases) after observing $g^U_{j,t} = 0$ ($g^U_{j,t} = 1$),*

$$p^U_{i,t+1}(g^U_{j,t} = 0) \equiv \mathbb{P}(g^U_{i,t+1} = 1 | h_t, g^U_{j,t} = 0) < p^U_{i,t} < p^U_{i,t+1}(g^U_{j,t} = 1) \equiv \mathbb{P}(g^U_{i,t+1} = 1 | h_t, g^U_{i,t} = 1). \quad (3)$$

Therefore, an SU bank failure makes market participants less confident about the universal government guarantee and, therefore, less optimistic about the government guarantee that will be extended to any SU bank. This belief updating results in an *implicit non-guarantee*; that is, $p^U_{i,t+1}(g^U_{j,t} = 0) < p^U_{i,t}$. As will soon be clear, this belief updating can have significant impacts on debt pricing and price efficiency.

Next, we present a numerical example to demonstrate the impact of a single observation of no government bailout on market confidence in future government guarantees.

Example 1 (Information Updating under Strong Anticipation of Government Bailout)**.** *The strong implicit guarantees in China feature a strong prior belief about a universal guarantee provided by the central bank ($p_0 = 95\%$) and local governments ($\eta = 20\%$), whereas the probability of not receiving a bailout conditional on a universal guarantee ($g = 1$) is extremely low ($\tau = 1\%$). In this case, the initial perceived likelihood of a government bailout is $p^U_{j,1} = 95.3\%$ for any SU bank j. Following a single observation of no bailout ($g^U_{i,t=1} = 0$), the perceived likelihood of a government bailout decreases to $p^U_{j,t=2} = 39.96\%$. Even with another observation of bailout ($g^U_{i,t=2} = 1$), this perceived probability will be $g^U_{i,t=2} = 62.05\%$, which is significantly lower than the initial value.*

Pricing Bank Debt

As the market changes its belief about a government guarantee that will be extended to all SU banks, the market will price the debt issued by SU banks differently. To examine the impact of an implicit non-guarantee on credit spreads, consider the following stylized setting. An SU bank i, which has a default probability $\phi_i \in (0, 1)$ and a recovery rate $\delta_i \in (0, 1)$, issues a debt at time $t + 1$ with principal that is normalized to 1. The maturity of the debt is normalized to 1 unit of time, and the risk-free rate is normalized to 0. Upon maturity, creditors get the promised interest $r_{i,t+1}$ plus the principal 1 conditional on no default, and get δ_i in case of default. Government guarantees, if provided, ensure a full repayment (or $1 + r_{i,t+1}$) even when the bank defaults.

Therefore, given the perceived likelihood of guarantee $p^U_{i,t+1}$, risk-neutral creditors in a competitive market would require an interest rate $r^U_{i,t+1}$ such that[26]

$$(1 + r^U_{i,t+1}) \left(1 - \phi_i(1 - p^U_{i,t+1})\right) + \delta_i \phi_i (1 - p^U_{i,t+1}) = 1. \tag{4}$$

It is worth noting that the above break-even condition is dependent on creditors' belief about a government guarantee (or $p^U_{i,t+1}$) — that is, how the implicit non-guarantee changes debt pricing. In fact, throughout the model, we consider the default risk ϕ_i and the recovery rate δ_i to be fixed in order to focus our attention on the impact of an implicit guarantee.

The interest rate that makes the creditors of SU bank i break even is

$$r^U_{i,t+1} = \frac{1 - \delta_i}{\frac{1}{\phi_i(1 - p^U_{i,t+1})} - 1}. \tag{5}$$

Note that, as the risk-free rate is normalized to 0, $r^U_{i,t+1}$ also represents the credit spread. Therefore, because of the implicit non-guarantee (i.e., $p^U_{i,t+1} < p^U_{i,t}$), the credit spreads on debts issued by any SU bank will increase following the failure of another SU bank; that is, $r^U_{i,t+1} > r^U_{i,t}$. This is simply because

$$\frac{\partial r^U_{i,t+1}}{\partial p^U_{i,t+1}} = -\frac{(1 - \delta_i)\phi_i}{\left(1 - \phi_i(1 - p^U_{i,t+1})\right)^2} < 0.$$

The following proposition summarizes this result.

Proposition 2 (Credit Spreads and Bank Failure)**.** *Following the failure of an SU bank j (i.e., $g^U_{j,t} = 0$), the credit spreads on debts issued by any SU bank i at $t + 1$ increase (i.e., $r^U_{i,t+1} > r^U_{i,t}$).*

Notably, as we assume that the guarantee will always be extended to SI banks (i.e., $p^I_{i,t+1} = 1$), the interest rate that an SI bank needs to pay is no different from the risk-free interest rate.

[26] Assuming the creditors are risk averse will not make any qualitative change to our results, although it adds to the complexity of solving the interest rates.

Price Efficiency

Next, we examine how an implicit non-guarantee affects pricing efficiency in the market of bank debts. First, note that, in the limiting case in which the market believes that a government bailout is guaranteed (i.e., $p^U_{i,t+1} = 1$), the credit spread is fixed at 0 (see (4)). This implies that the market price is completely insensitive to the credit risk and, thus, fails to reflect any of the borrower's risk. However, as long as $p^U_{i,t+1} < 1$, the credit spread increases with ϕ_i (see (5)), or, equivalently, $\frac{\partial r^U_{i,t+1}}{\partial \phi_i} > 0$. Intuitively, price efficiency improves if debt pricing is more sensitive to credit risk and, thus, more effectively reflects the borrower's risk.

To better understand how pricing efficiency is affected by the perceived strength of the government guarantee, we examine how the credit spread's sensitivity to credit risk is affected by the belief of the government guarantee $p^U_{i,t+1}$. Formally, we observe that

$$\frac{\partial^2 r^U_{i,t+1}}{\partial \phi_i \partial p^U_{i,t+1}} = -(1-\delta_i)\frac{1+\phi_i(1-p^U_{i,t+1})}{\left(1-\phi_i(1-p^U_{i,t+1})\right)^3} < 0,$$

which implies that a stronger belief in the government guarantee makes the credit spread less sensitive to credit risk, thereby reducing price efficiency. The next proposition summarizes how an implicit non-guarantee (i.e., $p^U_{i,t} > p^U_{i,t+1}$) changes price efficiency.

Proposition 3 (Price Efficiency and Bank Failure)**.** *Following the failure of an SU bank j (i.e., $g^U_{j,t} = 0$), the credit spread $r^U_{i,t+1}$ for debts issued by any SU bank i is more sensitive to credit risk ϕ_i compared with the sensitivity of $r^U_{i,t}$ to ϕ_i; that is,*

$$\left.\frac{\partial r^U_{i,t+1}}{\partial \phi_i}\right|_{p^U_{i,t+1}} > \left.\frac{\partial r^U_{i,t}}{\partial \phi_i}\right|_{p^U_{i,t}}. \tag{6}$$

Therefore, an implicit non-guarantee improves price efficiency.

3.2 Hypotheses Development

Our theoretical analyses demonstrate how an implicit government guarantee can have a significant effect on debt pricing and price efficiency. However, the implicit guarantee is not directly observable or easily quantifiable. Below, based on our theory, we develop testable hypotheses to guide our empirical analyses.

Hypothesis 1 (Credit Spreads)**.** *The failure of an SU bank increases the credit spreads on debts issued by SU banks, but not for debts issued by SI banks.*

Hypothesis 1 is directly from Proposition 2. The failure of an SU bank will induce an implicit non-guarantee (i.e., $p^U_{i,t+1} - p^U_{i,t} < 0$), which, in turn, leads to an increase in the credit spread on debts issued by SU banks — that is,

$$r^U_{i,t+1} - r^U_{i,t} \approx \frac{\partial r^U_{i,t}}{\partial p^U_{i,t}} \times \underbrace{\left(p^U_{i,t+1} - p^U_{i,t}\right)}_{\text{implicit non-guarantee}} > 0. \tag{7}$$

As debts issued by SI banks do not follow this pattern, the credit spread gap between SU and SI bank debt widens.

By Proposition 3, an implicit non-guarantee increases spread-risk sensitivity and, consequently, price efficiency. Notably, observing an increase in credit spreads on debt issued by a single bank does not necessarily imply an improvement in pricing efficiency, even when credit risk is controlled. This is simply because a variety of other factors (e.g., creditors' preference or market uncertainty) could explain the increase in the credit spread. Nonetheless, the following hypothesis translates this theoretical result to an empirically testable prediction.

Hypothesis 2 (Price Efficiency)**.** *The failure of an SU bank widens the spreads between debts issued by banks with varying credit risks. This pattern is unique to SU banks and does not apply to SI banks.*

To illustrate this underlying logic, consider two SU banks, i and k, which are identical in all other respects except for credit risk. Assume bank i carries a greater credit risk than bank k (i.e., $\phi_i > \phi_k$). If the implicit non-guarantee mechanism is in effect, then, based on Proposition 3, we should anticipate a widening of the difference in credit spreads between bank i and bank k following an observed failure of another SU bank and the resulting implicit non-guarantee. That is,

$$\left(r^U_{i,t+1} - r^U_{k,t+1}\right) - \left(r^U_{i,t} - r^U_{k,t}\right) \approx \underbrace{\left(\left.\frac{\partial r^U_{i,t+1}}{\partial \phi_i}\right|_{p^U_{i,t+1}} - \left.\frac{\partial r^U_{i,t+1}}{\partial \phi_i}\right|_{p^U_{i,t}} \right)}_{\text{an increase in spread-risk sensitivity}} \times (\phi_i - \phi_k) > 0 \tag{8}$$

4 Data and Summary Statistics

4.1 Sample Selection

We focus on the primary market of NCDs and collect daily issuance information and quarterly bank characteristics mainly from Wind Information Co. (WIND), a major financial data provider in China. For the part of the event study, the stock return data are from the China Stock Market & Accounting Research (CSMAR) Database. On May 24, 2019, the PBOC and CBIRC announced the takeover of Baoshang Bank, so our sample period is from October 1, 2018, to December 31, 2019, with a two-quarter window before and after the event date, respectively.[27].

In the main analyses, our sample universe is NCDs that issued successfully.[28] To exploit the variation in cross-bank credit spreads induced by the unanticipated Baoshang collapse, our focus is the bank-day-level analysis. We first merge the daily NCD issuance data with the quarterly bank characteristics, and then we apply the following screening criteria in our data analysis. We keep the NCD issuance sample with the largest issuance size if a bank issues more than one NCD on the same day.[29] We further drop the issuing dates if there are less than five NCDs issued by both SU and SI banks. For the missing quarterly bank characteristics (e.g., bank's total assets) obtained from the bank's balance sheet, we use the next non-missing values to fill the gap within the same calendar year. To alleviate the impact of troubled banks around the event, we remove samples of Baoshang Bank, Bank of Jinzhou, and Hengfeng Bank.[30] To minimize the effect of outliers in regressions, we truncate all continuous independent variables at the 1st and 99th percentile levels. To this end, our sample covers 473 unique banks with 21,368 bank-day observations.

[27]We restrict our sample to the end of 2019 in order to rule out some potential concerns caused by the COVID-19 pandemic. For robustness, we change our sample period in Section 8.2

[28]This choice could potentially result in selection bias. We will discuss this issue in detail in Section 8.1.

[29]We are using this method for two reasons. First, we primarily concentrate on the bank-day-level analysis. Second, the security-day-level data have only one-period observations without any time variation since we restrict our analysis to the primary market. In this step, we delete 12,635 security-day observations, which accounts for about 36.9% of total observations. In the robustness check, we also conduct analysis on the security level in Section 8.3.

[30]See the detailed discussion in Section 2.3.

4.2 Construction of Credit Spreads

The main dependent variable of our analysis is the credit spreads on the NCD issuance ($Spread_{it}$), which is calculated as the difference between the issuance rate on the NCD and Shibor interest rate with the same term to maturity on the same day. In our empirical analysis, the SU banks certified by PBOC are defined as *treatment banks*, and other banks are considered as the *control group*.[31] The event date is May 24, 2019, when Baoshang Bank was taken over, and $Post_t$ is a dummy equal to one if it is after the event and zero otherwise. Detailed definitions of other main variables are reported in Table B1 in the Appendix.

Figure 2 provides suggestive evidence that the shock increased the credit spreads for SU banks while having little influence on SI banks. Panel A of Figure 2 compares the simple average of daily credit spreads issued by SU and SI banks from October 1, 2018, to December 31, 2019, while Panel B of Figure 2 plots the NCD actual issuance size-weighted average. Panels A and B of Figure 2 both suggest that the event of Baoshang's collapse pushed up the differences in NCD issuance interest rates between the SU and SI banks, and the differences are quite persistent.

[Figure 2 About Here]

4.3 Summary Statistics

The summary statistics for the main variables are presented in Table 1. Credit spreads, issuance size, and duration of NCDs are all observed on a bank-day basis, while all other variables are measured quarterly. In Panel A, we present summary statistics for the entire sample period, which covers 455 SU banks and 18 SI banks, from October 1, 2018, to December 31, 2019. The mean and median of total assets are 667 and 122 billion RMB, respectively, which suggests that the total assets of banks are right skewed. The average debt-to-asset ratio of Chinese banks is 92%.

[31] On October 15, 2021, the PBOC released a list of systemically important banks in China. See the People's Bank of China, http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/4360688/index.html for details. According to the PBOC, there are 19 systemically important banks listed in Table A1. In our analysis, we only have 18 SI banks in our control group, since the Industrial and Commercial Bank of China, ranked the largest bank around the world by total assets in 2018, did not issue any NCDs during our sample period.

The mean and median of the actual NCD issuance size are 706 and 290 million RMB, respectively. This indicates that the issuance size is right skewed, which corresponds to the size distribution of bank assets. The average maturity of the issued NCDs in our sample is 0.538 years, indicating that NCDs are mostly short term. During our sample period, the average daily credit spreads on NCDs were 27.8 bps, with a standard deviation of 30.7 bps. The NCDs issued by SI (SU) banks account for approximately 16.3% (83.7%) of the total number of NCD issuance.

Panel B of Table 1 compares SU banks to SI banks during the pre-event period. Before this event, SI banks had 22.2 bps lower credit spreads than SU banks, which is a significant difference at the 1% level. Furthermore, NCDs issued by SI banks have a larger scale and a longer maturity, compared with those issued by SU banks. On average, SU banks have 5.976 trillion RMB fewer total assets and a debt-to-asset ratio that is 0.494 percentage points lower than SI banks. In terms of bank fundamentals, SU banks have a better return on assets ratio (ROA), capital adequacy ratio (CAR), and liquidity ratio than SI banks during the pre-event period, but a worse non-performing loan ratio (NPL).

[Table 1 About Here]

5 The Impact of Baoshang's Collapse on the NCD Market

We begin by investigating the effect of the Baoshang event on credit spreads on successful debt issuance and the rate of successful issuance in the NCD market. Recall that our theory predicts that the failure of Baoshang Bank would have a differential effect on the market belief in government guarantees for SI and SU banks, and thus on the pricing of bank debt. As a result, we divide the samples into SU (*treatment* group) and SI (*control* group) banks and examine the impact of Baoshang's collapse using the difference-in-differences (DiD) methodology.

5.1 Credit Spreads

Hypothesis 1 indicates that if the implied non-guarantee channel through which a bank failure affects debt pricing is in force, we should observe an increase in credit spreads on NCDs issued by SU banks following Baoshang's collapse, but not for NCDs issued by SI banks.

Figure 2 provides some preliminary evidence that the differences in credit spreads on NCD issuance between SU and SI banks are quite stable before this event. SI banks enjoy an average of 22.2 bps lower credit spreads during the pre-event period.[32] However, Baoshang's collapse significantly increased the credit spreads for SU banks while leaving them largely unchanged for SI banks. As a result, the difference in credit spreads between the two groups of banks significantly widened after this event. On average, this difference increased by 22.1 bps, reaching 44.3 bps.

It is important to note that the widening of the difference in NCD credit spreads is not a temporary market response. Rather, as can be seen in Figure 2, this gap persists. It lasts until December 2019, seven months after Baoshang's collapse, which is the end of our time window.[33]

To formally test Hypothesis 1, we conduct the following DiD regression model:

$$Spread_{it} = \beta_0 + \beta_1 Treat_i \times Post_t + X_{it}\Gamma + \mu_i + \lambda_t + \epsilon_{it}, \tag{9}$$

where the subscripts i and t denote bank and day, respectively. The dependent variable $Spread_{it}$ is the difference between the issuance interest rate on the NCD issued by bank i and the Shibor interest rate with the same term to maturity on the same day t. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if date t is after the event day and zero otherwise. X_{it} stands for a vector of time-varying and bank-specific control variables, μ_i and λ_t are the bank fixed effect and day fixed effect, respectively, and ϵ_{it} is the bank-day specific error term. β_1 is our main parameter of interest, and we expect the estimate of β_1 to be positive, as predicted by Hypothesis 1.

Table 2 reports the baseline regression results as specified by Equation (9). We start with a parsimonious model that only adds bank and day fixed effects in Column (1) of Table 2. The estimate of β_1 in Column (1) is positive and statistically significant at the 1% level, which indicates that the SU banks suffer a 21.9 bps increase in the credit spreads on NCD issuance relative to the SI banks after Baoshang's collapse.

[32] It is worth noting that the majority of SI banks are state-owned or joint-stock commercial banks with larger total assets. Lower financing costs are common among these banks, which may or may not be related to the implicit guarantee. The factors that contributed to the credit gap between SU and SI banks prior to Baoshang's collapse are beyond the scope of this research.

[33] In Figure OA.1 of the Online Appendix, we plot the daily average credit spreads on NCD issuance for SU and SI banks, extending our sample from October 1, 2017, to December 31, 2020, and the gap still exists.

This increase is of an economically significant magnitude since the mean of credit spreads for the SU banks is 21.4 bps in the pre-event period. In Column (2), we add two security-level controls, including the actual issuance size and term-to-maturity of the NCD; and in Column (3), we further control for some bank-level characteristics: the logarithm of total assets, the debt-to-asset ratio, and the credit rating. The key observation is that the estimate of β_1, in either column, is statistically significant at the 1% level and is very close to the estimator in Column (1) in terms of magnitude. Additionally, the results in Column (3) show that NCD issuance of a smaller issuance scale and longer term-to-maturity is associated with larger credit spreads. Also, banks with larger total assets and lower debt-to-asset ratios usually enjoy a more favorable credit spread.

[Table 2 About Here]

5.2 The Dynamic Impact on Credit Spreads

The causal inference in DiD is valid only under the "parallel trend" assumption. This assumption implies that, in the absence of Baoshang's collapse, the trends in credit spreads are identical for the treatment and control groups. Without any controls, Figure 2 presents some preliminary evidence that supports this assumption. Next, we run the following regression to validate the parallel trend assumption by including a series of dummy variables:

$$Spread_{it} = \alpha + \sum_{t=-90}^{90} \beta_t Treat_i \times RelativeDay_t + X_{it}\Gamma + \mu_i + \lambda_t + \epsilon_{it}, \tag{10}$$

where $RelativeDay_t$ is a dummy equal to one if the observation is on the t-th day relative to the event day. At the end points, $RelativeDay_{-90}$ equals one for all days that are 90 or more days before the event, while $RelativeDay_{90}$ equals one for all days that are 90 or more days after the event.[34] Other variables are the same as those in Equation (9). We follow standard procedures by excluding the relative time indicator for the period before the event. This approach enables us to estimate the dynamic effects of Baoshang's collapse on the credit spreads relative to the day before the shock.

[34] In the DiD analysis with an event study specification, we consider a 90-day window around the event because (1) a too short window is insufficient to capture the dynamic impact, and (2) a too long window may incorporate too much noisy variation in credit spreads given that our data are on a daily frequency. In Figure OA.2 of the Online Appendix, we change the time window, and the results are quite robust.

Figure 3 plots these coefficient estimates and the 95% confidence intervals, whereby standard errors are clustered at the bank level. As shown, the coefficient estimates for $Treat \times RelativeDay$ are insignificantly different from zero for almost all days before the event day, with no trends in credit spreads prior to the event. However, the differences in the credit spreads between SU and SI banks increase immediately following the shock. The impact of Baoshang's collapse on credit spreads on NCD issuance grows for about 20 days after the shock, and then the effect levels off, indicating a steady-state increase of about 26.9 bps in the differences in the credit spreads on NCD issuance between the two groups of banks. In sum, changes in the credit spread gap between SU and SI banks do not precede the event date, and Baoshang's collapse has a persistent level effect on the credit spread gap but does not have a trend effect. This also validates the parallel trend assumption and establishes that the DiD regression produces reliable estimates of the effect of Baoshang's collapse on the credit spread gap between SI and SU banks.

[Figure 3 About Here]

5.3 Success or Failure on NCD Issuance

Thus far, our examination of Hypothesis 1 has been limited to the sample in which the actual issuance size of NCDs is strictly positive. However, in some instances, the actual issuance size is zero, indicating that the issuing bank failed to raise any money.[35] In this section, to examine the impact of Baoshang's collapse on the failure of NCD issuance, we introduce two variables to proxy for the issuance success rate. The first one is a dummy variable, $IsSuc_{i,t}$, which indicates whether the NCD issuance for bank i at time t is successful or not. We say that the issuance of the NCD failed, $IsSuc_{i,t} = 0$, if and only if the *actual* issuance size given that bank i issues NCDs at date t is 0; otherwise, the issuance succeeds and $IsSuc_{i,t} = 1$. The second one is a continuous variable, $SucRaio_{i,t}$, which is calculated as the ratio of the actual issuance size to the planned issuance size.

Notably, Hypothesis 1 makes predictions about the prices — credit spreads on NCDs — but not about the quantities — the actual issuance sizes. However, if we interpret the zero issuance size as creditors requesting an unreasonably high credit spread, then, based

[35]Note that our results are subject to survivor bias because they are based on a sample with successful NCD issuance. In Section 8.1, we discuss this issue in detail and show that it actually strengthens, rather than weakens, our main results.

on the underlying logic of Hypothesis 1, we would expect more issuance failures for SU banks relative to SI banks in the aftermath of Baoshang's collapse.

To test this conjecture, we first present the time-varying changes in the success of issuance for SU and SI banks in Figure 4. Specifically, Panel A of Figure 4 plots the daily average of $IsSuc_{i,t}$, which captures the percentage of successful NCD issuance at each date t. We sometimes refer to this average as the *success rate*. As illustrated in Panel A of Figure 4, these success rates are extremely volatile. This is because the number of SU or SI banks issuing NCDs varies significantly from day to day. For that reason, we create the series of an n-day moving average of $IsSuc_{i,t}$.[36] Panel B of Figure 4 plots the mean of $IsSuc_{i,t}^{MA(15)}$.[37]

The key observation is that the success rate on NCD issuance declines significantly for SU banks following Baoshang's collapse, but that rate remains stable for SI banks. A similar data pattern can be found for the other variable, *SucRatio*, as can be seen in Panels C and D of Figure 4 .

[Figure 4 About Here]

Next, we perform a DiD estimation similar to Equation (9) but with the measures of issuance success as the dependent variable. Table 3 summarizes the findings. Take *IsSuc* for example. Column (1) of Panel A controls for only bank and day fixed effects, and the coefficient estimate for $Treat \times Post$ is -0.063 and is significant at the 1% level, indicating that the chance of successful issuance following the event decreases 6.3 percentage points more for SU banks than for SI banks. Column (2) of Panel A contains the same controls as Equation (9), except that the actual issuance size is replaced by the planned issuance size,[38] and Columns (3), (4), and (5) of Panel A set the dependent variables as the 5-day, 10-day, and 15-day window of the moving average of *IsSuc*, respectively. All coefficient estimates for $Treat \times Post$ are negative and statistically significant at the 1% level. In addition, we use *SucRatio* as another proxy for issuance success and observe similar results in Panel B of Table 3. For example, the coefficient estimate for $Treat \times Post$ in Panel B of Table 3 is -10.341 and is significant at the 1% level, suggesting that SU banks can fund

[36] In detail, an n-day moving average of $IsSuc_{i,t}$ is $IsSuc_{i,t}^{MA(n)} \equiv \frac{1}{n}\sum_{u=t-n+1}^{t} IsSuc_{i,u}$.

[37] In addition, we use a 5-day or 10-day moving average window for robustness, and we observe that this data pattern is insensitive to changes in the length of the moving average window.

[38] We do this because some observations have zero actual issuance size when we expand our sample universe.

about 10.3 percentage points less of the planned issuance size following the event, compared with SI banks. The negative coefficient estimates for $Treat \times Post$ are all significant at the 1% level in Columns (2)-(5) of Panel B.

[Table 3 About Here]

In sum, we find that following the Baoshang event, both the probability of a successful NCD issuance and, conditional on successful issuance, the amount of money successfully raised by SU banks relative to the planned size decreased significantly, whereas none of these patterns hold true for SI banks. This implies that the systemic importance of a particular bank is critical in explaining the impact of the Baoshang event. Combined with the observed change in credit spreads, results from our empirical analyses confirm Hypothesis 1 that the implicit non-guarantee induced by the observation of an SU bank's failure will have a detrimental effect on the funding condition of other SU banks while having no effect on the funding condition of SI banks.

5.4 More Evidence: Mutual Fund Holdings

Next, we present some direct evidence that investors treat NCDs issued by SU banks differently than those issued by SI banks in the aftermath of Baoshang's collapse. Data limitations prevented us from being able to track daily purchases or holdings of NCDs by any type of investor. For that reason, we resort to quarterly mutual fund disclosures of the top 10 (or top 5) holdings of fixed-income securities. Notably, mutual funds, particularly money market funds, are a significant player in the NCD market, and both bond funds and hybrid funds make investments in the NCD market.[39]

In our data analyses, we examine the reported holdings of NCDs issued by SI or SU banks before and after Baoshang's failure.[40] Our conjecture is that the implicit non-guarantee induced by Baoshang's collapse would dissuade fund managers from holding NCDs issued by SU banks, but not those issued by SI banks. The underlying reason is that the implicit non-guarantee applies only to SU banks and not to SI banks.

[39] According to the Asset Management Association of China, bond and hybrid mutual funds should disclose the detailed bond holdings of the top 5 ranked by market value in their quarterly reports, and money market mutual funds should disclose the detailed bond holdings of the top 10 ranked by market value in their quarterly reports.

[40] It is worth noting that, while our primary empirical analysis focuses on NCD issuance, implicit non-guarantees should have a similar effect on outstanding NCDs.

Using the quarterly disclosed top 10 (or top 5) bond holdings data, we construct several measures directly related to fund managers' holdings of NCDs issued by SU and SI banks. We first calculate the logarithm of the total holding values of NCDs issued by SI ($s = I$) or SU ($s = U$) bank for fund j at time t, $LnHV_{sjt}$. Likewise, we then compute, for each fund j at time t, the ratio of the total holding values of NCDs issued by SI or SU banks to fund j's total holding values of NCDs, $HVRatio_{sjt}$, and the ratio of the total holding values of NCDs issued by SI or SU bank to fund j's net asset value, $OfNAV_{sjt}$.

[Table 4 About Here]

Results are reported in Table 4. The coefficient estimates for *Treat* $\times$ *Post* in all columns are negative and statistically significant at the 1% level, indicating that, in the aftermath of Baoshang's collapse, mutual fund managers unloaded more NCDs issued by SU banks relative to those issued by SI banks. These effects are also economically large. For example, the coefficient estimate for *Treat* $\times$ *Post* in Column (1) is -0.270, suggesting that, on average, mutual fund managers decreased their holding values of NCDs issued by SU banks by 27.0%, compared with those issued by SI banks after Baoshang's collapse.

From the funding holdings data, we find some direct evidence documenting how the financial market responded to Baoshang's collapse. The evidence that fund managers significantly reduced their holdings of NCDs issued by SU banks in comparison to NCDs issued by SI banks further demonstrates that the systemic importance is a critical factor in understanding the market response. Interestingly, when combined with evidence from credit spreads and the success rate on NCD issuance, our empirical findings suggest that the implicit non-guarantee can be the underlying reason for the observed debt "runs." This, in turn, significantly harmed SU banks' liquidity positions, resulting in severe liquidity distress for some of them — for example, Bank of Jinzhou.

6 Mechanism: Implicit Non-Guarantee

Thus far, we have discovered that funding conditions in the NCD market deteriorated significantly following Baoshang's collapse. Specifically, credit spreads on NCD issuance increased, and some issuing banks failed to raise any money. Interestingly, when banks are classified according to their systemic importance, our empirical analyses in Section 5 clearly demonstrate that the deterioration in funding conditions was primarily a result of market reactions to SU banks, whereas the market environment remained relatively stable for SI banks. This is consistent with our theoretical prediction that Baoshang's collapse would result in an implicit non-guarantee — a diminished confidence in government guarantees extended to SU banks, thereby impairing the SU banks' funding conditions.

However, we cannot take it for granted that the implied non-guarantee is the only channel through which the failure of Baoshang Bank can affect other banks. After all, SU and SI banks may differ in many other aspects beyond their systemic importance, and their responses to the bankruptcy of a peer bank may be markedly different and related or unrelated to the systemic importance factor. That said, there could be other possible explanations for the observed data pattern. In this section, we discuss these alternative channels.

6.1 Changes in Bank Fundamentals and Credit Risks

One potential concern is that the bankruptcy of Baoshang Bank could have an adverse impact on other banks' fundamentals through various (direct or indirect) financial connections. This may increase the credit risks of other banks, and the effect of fundamental-based contagion varies according to the nature of the banks' financial connections. As such, the change in debt pricing may simply reflect the effect of Baoshang's collapse on other banks' credit risk, even if the perceived government guarantee remains unchanged. A lack of data revealing Baoshang's direct and indirect financial connections with other banks prevented us from directly observing and comparing the intensities of this "contagion" mechanism.

However, if this channel can explain the observed difference in credit spread changes between SI and SU banks, we should observe that Baoshang's collapse has a more pronounced negative impact on SU banks' fundamentals relative to SI banks. We first run the following regression to determine whether the impact of Baoshang's collapse on bank fundamentals varies significantly between SI and SU banks:

$$Fundamental_{it} = \beta_0 + \beta_1 Treat_i \times Post_t + X_{it}\Gamma + \mu_i + \lambda_t + \epsilon_{it}, \tag{11}$$

where the subscripts i and t denote bank and quarter, respectively. The dependent variable $Fundamental_{it}$ is bank i's fundamental variables at date t, including the return on assets ratio (ROA_{it}), the non-performing loan ratio (NPL_{it}), the capital adequacy ratio (CAR_{it}), and the liquidity ratio ($LiquidRatio_{it}$). $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if date t is after the event date and zero otherwise. X_{it} stands for a vector of time-varying and bank-specific control variables, including the logarithm of total assets ($LnTotalAsset_{it}$), debt-to-asset ratio ($DebtAssetRatio_{it}$), and credit rating ($Rating_{it}$). μ_i and λ_t are the bank fixed effect and quarter fixed effect, respectively. ϵ_{it} is the bank-quarter specific error term. β_1 is the primary parameter that we are interested in. If the failure of Baoshang has a greater adverse effect on SU banks relative to SI banks, we would expect the estimate of β_1 to be statistically significant and negative for ROA, CAR, and the liquidity ratio, and positive for NPL.

[Table 5 About Here]

Results in Table 5 show that the coefficient estimates for $Treat \times Post$ are all statistically insignificant in Columns (1)-(3), indicating that there is no significant difference in the changes in bank fundamentals following the event, including ROA, NPL, and CAR, between SU and SI banks. As a result, the changes in bank fundamentals and credit risks cannot account for the observed spread difference in credit spreads.

Notably, the estimate of β_1 in Column (4) is -1.631, which is statistically significant at the 1% level. This implies that the ratio of liquid assets to total assets associated with SU banks is reduced by 1.631 percentage points more than the ratio associated with SI banks following Baoshang's collapse. This is likely to be a result of the deterioration in funding conditions (i.e., difficulties with NCD issuance and increased credit spreads) that SU banks encountered following the event, as discussed in Section 5.

However, it is also possible that the Baoshang event results in a market-wide liquidity shortage that disproportionately affects SU banks compared to SI banks, and that the liquidity reasons account for the observed difference in the credit spread change between SI and SU banks. We will discuss this possible explanation in detail in the following section.

6.2 Market-wide Liquidity Shortage

In this section, we address the concern that the observed pattern in credit spread changes across SI and SU banks may be related to the deterioration in market liquidity conditions following Baoshang's collapse. First, as can be seen in Figure 2, the increased gap between SU and SI banks in the credit spreads is persistent and lasting, remaining stable in magnitude for more than six months. Given that the liquidity problems should be temporary, it is hard to believe that this sustained gap is the result of a liquidity shortage. Further, as discussed in Section 2, the PBOC implemented a variety of measures, including massive liquidity injections to maintain market-wide liquidity.[41] However, even though the PBOC provided ample liquidity, the upward trend in the credit spread gap between SU and SI banks continued for about 20 days after the shock, and the gap has remained quite persistent since then. This further demonstrates that liquidity considerations are unlikely to be the driving force behind the observed increase in the credit spread gap.

We further conduct a placebo test to ascertain whether the observed data pattern is primarily driven by the liquidity shortage. On October 25, 2016, it was rumored that the PBOC intended to incorporate off-balance-sheet wealth management products (hereafter, WMPs) into the monitoring checklist of the macroprudential assessment (MPA) framework,[42] which we refer to as the "WMP event." WMPs are short-term off-balance-sheet products offered by banks to retail investors as substitutes for deposits. They are a form of regulatory arbitrage that enables banks to evade stringent off-balance-sheet regulations (e.g., the loan-to-deposit ratio).[43] This news has the potential to have a significant impact on market liquidity, as banks and other financial institutions in China rely heavily on WMPs to meet their liquidity needs (Acharya et al., 2021).

We employ the Baidu search index — China's most popular search engine — to confirm that October 25, 2016, was the date on which this rumor of "stricter regulations on WMPs" garnered widespread attention. Figure 5 plots the number of online searches in Chinese for the terms "off-balance-sheet wealth management products" and "macro prudential assessment" on Baidu from September 1, 2016, to January 31, 2017. The amount of attention paid to both phrases increases dramatically on October 25, 2016, reaching its first peak the following day. A similar search volume pattern appears around the second peak, when the PBOC officially confirms the rumor.[44]

[41] See the detailed discussion in Section 2.3.

[42] For instance, this rumor was formally reported on October 26, 2016, by Tencent Finance. For details, see "Comment on the Central Bank's 'Notice on Including Off-Balance Sheet Wealth Management Business in the "Broad Credit" Calculation': The Impact of the Inclusion of Wealth Management Products in MPA is Very Small," Tencent Finance, October 26, 2016, https://finance.qq.com/a/20161026/031085.htm.

[43] Furthermore, unlike deposits, banks can freely adjust the interest rate on WMPs because they are not subject to the PBOC's deposit rate ceiling. See Acharya et al. (2021) for a more detailed discussion on WMPs.

[44] The PBOC officially confirmed the news on December 19, 2016, and announced that the new regulation would be implemented beginning in the first quarter of 2017, as reported by Reuters. See "China Central Bank to Count Off-Balance Sheet Wealth Management Products in Assessing Banks' Risk: Sources," Reuters, December 19, 2016, https://www.reuters.com/article/us-china-pboc-shadowbanking-idUSKBN14813

[Figure 5 About Here]

As a result, we choose October 25, 2016, as the date of our placebo event. After the rumor spreads, the market should anticipate a significant reduction in the size of WMPs once monitored and regulated under the MPA framework. That anticipation can cause the market to panic early. Panel A of Figure 6 confirms that the dissemination of this rumor immediately resulted in market-wide liquidity distress, as the three-month Shibor interest rate began to rise dramatically on October 25, 2016, and thereafter. In this sense, this placebo event is appropriate because it enables us to identify how a liquidity shortage affects the funding conditions in the NCD market, specifically the differences between SI and SU banks.

If the observed pattern in NCD credit spreads around Baoshang's collapse is entirely a result of market reactions to deteriorating liquidity conditions, then we should expect to see a pattern similar to that observed around the "WMP event." Nonetheless, the results in Figure 6 reveal a strikingly different pattern. As illustrated in Panel A of Figure 6, the liquidity distress increases credit spreads on NCD issuance for both SU and SI banks, with no discernible difference in magnitude.

Next, we conduct a formal analysis of the dynamic impact of the "WMP event" on credit spreads by employing DiD estimation with an event study design similar to Equation (10). As illustrated in Panel B of Figure 6, there is no immediate difference in credit spread changes between SU and SI banks following the "WMP event." Within 30 days after this event, the difference in credit spread changes between the two groups of banks increases only temporarily, lasting approximately 15 days in total.

In summary, the placebo test provides additional evidence to refute the alternative explanation that the difference in credit spread changes between SU and SI banks following Baoshang's collapse is mainly a result of its impact on liquidity conditions.

[Figure 6 About Here]

6.3 Sizes of Short-term Borrowing and Interbank Exposures

Another possibility is that SI and SU banks may adjust their financial positions differently in their endogenous response to Baoshang's collapse, and this could account for the

T for details.

observed difference in credit spreads on NCD issuance as well as the amount of money raised through NCD issuance.

Arguably, if SU banks borrow more from NCD issuance or from the interbank market than SI banks, the market may become unwilling to lend to SU banks in the NCD market, even if market perceptions of a government guarantee remain unchanged. Likewise, if SU banks borrow more short-term debt from the interbank market, exposing themselves to more rollover risk, then the market may require higher credit spreads for NCDs issued by SU banks. Further, if SU banks end up lending more to other banks, as compared with SI banks, then the increased exposure to counterparty risks might account for the observed market responses in the NCD market.

To address these concerns, we first calculate the total actual size of NCDs for each bank on a quarterly basis, followed by the logarithm of the total NCD size and ratio of total NCD size to total liability. Then, we run a DiD regression similar to Equation (11) by substituting these measures of NCD issuance size for the bank fundamentals. As shown in Table 6, our empirical evidence refutes the presumption that SU banks increased the size of NCD issuance more than SI banks in the aftermath of Baoshang's collapse. The coefficient estimates for $Treat \times Post$ in Columns (1) and (2) of Table 6 are negative and statistically significant at the 1% level, implying that SU banks reduce the total actual size of NCD issuance following the event more than SI banks do.

We take a further look at banks' total borrowing positions in the interbank market.[45] In our regressions, we use the logarithm of total interbank borrowing in Column (3) and the ratio of total interbank borrowing to total liability in Column (4), respectively. Both coefficient estimates for $Treat \times Post$ in Columns (3) and (4) are negative and statistically significant at the 1% level, indicating that the SU banks decrease their borrowings from the interbank market after the event more than the SI banks do. As a result, SU banks' overall short-term borrowing, including NCDs and interbank borrowing, decrease more following Baoshang's collapse, as compared with SI banks.

In addition, we also check banks' total lending positions in the interbank market,

[45] To clarify, the definitions of interbank borrowing and lending may be broader than those used in the classic literature. The data available to us allow us to examine only interbank exposures that meet these definitions. To be more precise, interbank borrowing here includes interbank loans, securities sold under repurchase agreements, debt payable, and deposits made by other banks and financial institutions; and interbank lending includes interbank loans (extended to other banks), securities purchased under repurchase agreements, and deposits with other banks and financial institutions. These definitions can also be found in Table B1 in Appendix B.

which capture the exposure to counterparty risks. Likewise, for each bank, we calculate the logarithm of total interbank lending in Column (5) and the ratio of total interbank lending to total assets in Column (6), respectively. Both coefficient estimates for *Treat* $\times$ *Post* in Columns (5) and (6) are negative and statistically significant at the 5% level, which suggests that the SU banks become more conservative relative to SI banks in terms of extending credit to other banks following Baoshang's collapse. As a result, SU banks overall have a lower exposure to counterparty risks following Baoshang's collapse, as compared with SI banks.

In summary, SU banks reduced their short-term borrowing more than SI banks, including NCDs and interbank borrowing. In addition, SU banks' exposure to the interbank market was reduced more relative to SI banks. This evidence tends to refute the presumption that the size of short-term borrowing and the exposure to counterparty risks account for the observed change in credit spreads on NCD issuance.

[Table 6 About Here]

6.4 Other Mechanisms that Increase Spread-Risk Sensitivity

Our theory highlights that the implied non-guarantee from Baoshang's collapse can make creditors more sensitive to the preexisting credit risks associated with SU banks (see Proposition 3). In this section, we consider other mechanisms that may increase spread-risk sensitivity. One possibility is that the failure of Baoshang serves as a wake-up call for NCD investors, raising their awareness of the risks associated with the issuing banks. It is also possible that investors became more risk averse after observing Baoshang's collapse, causing them to re-price banks' credit risks. Such mechanism makes debt pricing more sensitive to preexisting credit risks, and in this way, increases the credit spread difference between banks with lower credit risks and those with higher credit risks.

If any of these mechanisms work, then they will amplify the difference in credit spreads between banks with lower preexisting risks and those with higher preexisting risks. Therefore, if SU banks are more risky overall relative to SI banks before Baoshang's collapse, such a mechanism can account for the observed increased gap in the change in credit spreads across SU and SI banks. However, it is important to note that such mechanisms (e.g., the shifts in risk preferences and awareness) are entirely focused on credit risks and, thus, are independent of whether these risks are associated with SI or SU banks.

Therefore, these alternative explanations should be independent of banks' systemic importance.

Prior to Baoshang's collapse, there were indeed some fundamental differences between SU and SI banks, aside from the systemic importance factor. Panel B of Table 1 shows that on average, SU banks have higher ROA, CAR, and liquidity ratios than SI banks, implying that SU banks are better prepared for a crisis situation. SU banks, on the other hand, have a higher NPL ratio relative to SI banks, indicating that their outstanding bank loans are of lower quality. Recall that we have shown in Table 5 that there are no significant changes in ROA and CAR surrounding the Baoshang event between SU and SI banks. Combined with the fact that SU banks are not riskier than SI banks before the event in terms of ROA and CAR, it is unlikely that any other mechanism, which purely amplifies the preexisting risks, could work to explain the observed data pattern in the NCD market.

Next, we highlight the role of the systemic importance factor in understanding the impact of preexisting risks on the change in credit spreads on NCD issuance. We first divide all banks in our sample by the median of their fundamentals (i.e., ROA, NPL, and CAR) at the end of 2018, the year before the event.[46] Then, we rerun the regression in Equation (9) by replacing $Treat_i$ with $High_i$, which equals one if bank i's fundamental variable (ROA, NPL, or CAR) is above the median at the end of 2018 and zero otherwise. Results in Columns (1), (3), and (5) of Table 7 indicate that banks with stronger pre-event fundamentals experience significantly smaller changes in credit spreads on NCD issuance following the shock than banks with weaker pre-event fundamentals. This pattern holds true for all bank fundamentals measures, including ROA, NPL, and CAR. [47]

[Table 7 About Here]

Our key regression examines the interaction effect of preexisting risks and the systemic importance factor by incorporating interaction terms with the variable $Treat_i$. If

[46] As shown in Table 5, there are no significant changes in ROA, CAR, and NPL around the event between SU and SI banks. Nonetheless, the liquidity ratios of SU banks decreased more than those of SI banks following the event. Therefore, here we follow common procedures in the DiD approach and divide our sample based on the pre-event ROA, CAR, and NPL, but we do not consider the pre-event liquidity ratio.

[47] It is worth noting that this finding should not be taken as supportive evidence for changes in risk preference or awareness. As discussed, the implicit non-guarantee may also increase spread-risk sensitivity and therefore enables the preexisting risks to explain the observed change in credit spreads. This is in fact confirmed in Columns (2), (4), and (6) of Table 7, as well as in our discussion on price efficiency in Section 6.6.

the underlying mechanism is independent of the systemic importance factor, we should expect that only factors capturing preexisting risks, but not the one relating to systemic importance, will be statistically significant in explaining observed differences in credit spreads on NCD issuance.

Results of the regressions with these interaction terms are reported in Columns (2), (4), and (6) of Table 7. In Column (2), for example, the coefficient estimate for $Treat \times Post$ is positive and statistically significant at the 1% level. This means that within the low-ROA banks prior to the event, the changes in the credit spreads on NCD issuance following the shock are greater for SU banks than for SI banks. Moreover, the coefficient estimate for $Treat \times Post + High \times Post \times Treat$ in Column (2) is positive and statistically significant at the 1% level (F-statistics is 29.83), implying that the same data patterns between SU and SI banks are observed within the high-ROA banks. When we consider other fundamental measures, such as NPL and CAR, as shown in Columns (4) and (6) of Table 7, the results are qualitatively the same.

In sum, we conclude that the observed change in credit spreads cannot be explained by any mechanism that is unrelated to banks' systemic importance but acts as an amplifier of banks' preexisting risks. Rather, preexisting risks influence credit spreads following Baoshang's collapse through their interaction with the systemic importance factor.

6.5 More Discussions on Implicit Non-Guarantee

Summary Thus far, we have demonstrated that the observed pattern of credit spread changes in the NCD market is unlikely to be the result of (1) a liquidity shortage or other changes in bank fundamentals caused by this event, (2) banks endogenously increasing their amounts of short-term borrowing or their exposure to other banks in response to this event, and (3) other mechanisms that magnify spread-risk sensitivity (e.g., a shift in creditors' risk preferences or awareness). While it is impossible to rule out all possible explanations, the empirical evidence suggests that creditors' risk attitudes and awareness, as well as banks' credit risks associated with market-wide liquidity distress, rollover risks, and counterparty risks, cannot be the primary explanations for the observed data pattern in the NCD market surrounding Baoshang's collapse.

Implicit non-guarantee: further controlling bank fundamentals To validate the mechanism of implicit non-guarantee, we rerun our main regression (9) by additionally controlling for the above-mentioned bank fundamentals. Table 8 summarizes the findings. Column (1) of Table 8, which is identical to Column (3) of Table 2, is included here to facilitate comparisons. Columns (2)–(5) include additional control variables of ROA, NPL, CAR, and liquidity ratio, respectively. All coefficient estimates for $Treat \times Post$ are positive and statistically significant at the 1% level, with a magnitude very close to that in Column (1). Finally, in Column (6), we control all of the four variables that capture different aspects of bank fundamentals. The coefficient estimate for $Treat \times Post$ remains statistically significant at the 1% level, but becomes slightly smaller than that in Column (1). Based on our previous discussion, we attribute the 18.5 bps increase in the difference in changes of credit spreads following the event to the impact of implicit non-guarantee.

[Table 8 About Here]

Implicit non-guarantee as a "contagion" mechanism Taken together, the findings in our research thus far identify an interesting "contagion" channel — the implicit non-guarantee — through which the failure of one bank can cause a deterioration in the funding conditions of other banks. To be more precise, if the market anticipates that both Bank A and Bank B will receive government bailouts, the observation that Bank A enters a state of distress without receiving a bailout puts Bank B in a much worse position to raise money from its creditors. Our empirical findings indicate that it will trigger a market response that resembles debt runs, thereby increasing the cost of debt financing, reducing the likelihood of successful debt issuance, and consequently causing a significant deterioration in the liquidity conditions of affected banks. In the context of China, where government bailouts are a long-standing practice and have been universally applied to all banks, we provide evidence to demonstrate the significance of this *contagion* mechanism.

More importantly, this spillover mechanism is independent of other traditional contagion mechanisms, such as balance sheet contagion via direct or indirect financial connections, fire sales, or liquidity crises. In a crisis characterized by bank failures, other contagion channels may interact with the one of "implicit non-guarantee" to exacerbate the situation. However, as shown by Baoshang's collapse, even when other mechanisms of contagion are largely absent because of government intervention, an implicit non-guarantee can continue to have a detrimental effect on respective banks. Furthermore, as our empirical findings clearly demonstrate, the adverse impact of this spillover is not temporary, and traditional government interventions such as liquidity injections are likely to be ineffective at mitigating such a "contagion."

6.6 Price Efficiency

We end our discussion on the possible mechanisms by further examining the spread-to-risk sensitivity of NCDs issued by SU and SI banks before and after the Baoshang event. Hypothesis 2 clearly demonstrates that if the implicit non-guarantee is the mechanism underlying the observed data pattern in the NCD market, then the Baoshang event should increase the spread-to-risk sensitivity of NCD issuance for SU banks but not for SI banks. Here, to further validate the channel of the implicit non-guarantee, we conduct empirical analysis to test Hypothesis 2.

Fundamental Risks

A reasonable assumption is that fundamental measures such as ROA, NPL, CAR, and the liquidity ratio are correlated with and, thus, can be good proxies for banks' credit risks. To examine the change in spread-risk sensitivity and to test Hypothesis 2, we first consider these time-varying and bank-specific fundamental variables. Our findings are summarized in Table 9 with ROA and NPL in Panel A and CAR and the liquidity ratio in Panel B.

Take ROA for example. Here, we only include the SU banks in Column (1) and the coefficient estimate for ROA is statistically insignificant, while the coefficient estimate for $ROA \times Post + ROA$ is -0.324 and statistically significant at the 1% level (F-statistics is 35.91). This implies that, for SU banks, ROA has no impact on the credit spreads on NCD issuance before Baoshang's collapse, but it imposes a negative association with credit spreads afterward. Moreover, the negative coefficient estimate for $ROA \times Post$, which is statistically significant at the 1% level, implies that the negative association between ROA and credit spreads becomes significantly more pronounced after the event. However, as shown in Column (2), ROA does not play any role in determining the pricing of credit spreads either before or after this event for SI banks. Finally, in Column (3), we compare the sensitivity of credit spreads to ROA for both SU and SI banks. The coefficient estimate for $Treat \times Post \times ROA$ is negative and statistically significant at the 1% level, indicating that, in comparison to SI banks, credit spreads on NCD issuance are priced much more by ROA after the event for SU banks.

The regressions on other bank fundamentals — namely, NPL, CAR, and the liquidity ratio — exhibit a similar pattern, with the exception that the effect on the liquidity ratio is relatively weak. Our evidence indicates that, prior to Baoshang's collapse, credit spreads on both SU and SI banks were insensitive to banks' credit risks. This is consistent with the fact that the government previously extended bailouts to all banks, and the market anticipated that all banks would receive bailouts in the future. However, following Baoshang's collapse, the market begins to price credit risks associated with SU banks but not risks associated with SI banks.

Recall that, as shown in Section 6.1 and Table 5, the differences in these fundamental measures between SU and SI banks are stable overall. Therefore, the increased spread-risk sensitivity in fact largely accounts for the observed increase in the change in credit spreads between SI and SU banks.

[Table 9 About Here]

To summarize, we employ the DiD approach and demonstrate that the implicit non-guarantee induced by Baoshang's collapse increases spread-risk sensitivity by using bank fundamentals as proxies for banks' credit risks. In this way, price efficiency is improved. All of these findings are consistent with Hypothesis 2 and re-confirm that the underlying mechanism is the diminished confidence in the government guarantee of SU banks.

7 Impacts of Implicit Non-Guarantee

Because the implicit government guarantee and market perception of it are almost unobservable and unquantifiable, conducting empirical research on its consequences is exceedingly difficult. On the other hand, for countries such as China, where the banking system is heavily reliant on implicit government bailouts, it is critical for bank supervisors to understand the implicit guarantee's impact on the banking industry and the financial market in general.

Our theoretical and empirical analyses thus far demonstrate that the bankruptcy of Baoshang bank reduces confidence in the government bailout of SU banks but not SI banks. As a result, this setting enables us to investigate the consequences of implicit guarantee by examining the behavior and performance of SI and SU banks prior to and following Baoshang's collapse. In this section, we investigate the impacts of implicit guarantee on the equity market, banks' risk-taking behavior, and market discipline implemented by debt holders.

7.1 Stock Market Response

Next, we examine how stock market investors would respond to the implicit non-guarantee induced by the failure of Baoshang Bank. We consider all banks in our sample period that are public listed in the Chinese A-share stock market, which covers 13 listed SU banks and 17 listed SI banks in total.

To measure the stock market reactions to Baoshang's collapse, we calculate the cumulative abnormal return (CARet) centered on the event date on May 24, 2019, using two risk models: the market model and the market-adjusted return model. For the market model, we estimate the following regression to obtain the abnormal return:

$$Ret_{it} = \alpha_i + \beta_i RM_t + \epsilon_{it}, \tag{12}$$

where the subscripts i and t denote stock and day, respectively. Ret_{it} is the return on stock i on day t, and RM_t is the value-weighted market return on day t. The model is estimated for each bank over the 120-day window with a minimum of 30 observations prior to the event day to gain the estimators $\hat{\alpha}_i$ and $\hat{\beta}_i$.[48] Next, we can calculate the abnormal return as $ARet_{i\tau} = Reti\tau - (\hat{\alpha}_i + \hat{\beta}_i RM_{it})$ over the event window ($\tau = -n, \cdots, -1, 0, 1, \cdots, n$). Then the cumulative abnormal return is calculated as $\sum_{\tau=-n}^{n} ARet_{i\tau}$ using an n-day window around the event. For robustness, we use the market-adjusted return model to calculate the abnormal return, which is defined as the stock return minus the value-weighted market return. In addition, we also calculate the standardized cumulative abnormal return as

$$\frac{CARet_{it}}{\sqrt{N \times \sigma^2_{\epsilon_{ARet_i}}}}, \tag{13}$$

where the subscripts i and t denote stock and day, respectively. $CARet_{it}$ is the cumulative abnormal return from a risk model for stock i on day t, $\sigma^2_{\epsilon_{ARet_i}}$ is the variance of the residual from the risk model estimation for stock i, and N is the estimation window length.[49]

[48]Following standard procedure, we skip 10 trading days as the gap between the end of the estimation period and the beginning of the event window, to prevent the estimation window from including information that might have been leaked to the market well before the event.

[49]When events tend to cluster in calendar time (e.g., a growing demand for month-end liquidity),

Table 10 reports the event study results of Baoshang's collapse using different event windows. For the listed SU banks, there is a statistically significant and positive CARet within the 3-day event window (i.e., $\tau = -1, 0, 1$), which becomes negative from the 10-day to 60-day event windows. The 60-day event window of CARet is -14.231% (but insignificant) and -4.193% (significant at the 5% level) using the market model and market-adjusted return model, respectively. For the listed SI banks, the CARet is always positive regardless of whatever risk models and event windows are employed.

[Table 10 About Here]

The stock market has generally reacted negatively to the diminished market confidence in the government bailout following Baoshang's collapse. These adverse reactions affect only SU banks and not SI banks, as they are unaffected by the change in market confidence. This observation demonstrates that the expectation of a government guarantee is a significant factor in supporting the equity market valuation of SU banks in China.

7.2 Bank Risk-taking Behavior

Previous theoretical studies examine two effects of an implicit guarantee on banks' risk taking that work in opposite directions. The first one is the *moral hazard effect*: banks protected by the government bailout usually seek more risk taking since creditors have less incentive to monitor in the presence of an implicit guarantee (e.g., Flannery, 1998; Gropp, Vesala and Vulpes, 2006; Ruckes, 2004; Sironi, 2003). The second one is the *charter value effect*: banks with higher charter values resulting from government bailouts would decrease the incentives for risk taking because of the threat of losing future rents (e.g., Hakenes and Schnabel, 2010; Keeley, 1990). However, the net effect of an implicit guarantee on the risk taking of banks depends on the relative strength of the two channels. In our study, with a focus on the rise of the implicit non-guarantee in the Chinese banking system, we examine the impact of Baoshang's collapse on banks' risk taking. Specifically,

Boehmer, Masumeci and Poulsen (1991) employ the standardized cross-sectional test, which takes into account information from both the estimation and the event windows and allows for event-induced variance shifts. Boehmer, Masumeci and Poulsen (1991) demonstrate that their test statistic is not affected by event-induced variance changes. In our analysis, we calculate the standardized cumulative abnormal return and the corresponding t-statistics for a robustness check.

we follow Laeven and Levine (2009) in using the logarithm of the z-score ($LnZsocre_{it}$) and the volatility of ROA (Std_ROA_{it}) as banks' risk-taking measures.[50]

Results are shown in Table 11. The positive coefficient estimate for $Treat \times Post$ in Column (1) is significant at the 1% level, which means that, compared with SI banks, SU banks become much less inclined toward risk taking after Baoshang's collapse. The statistically significant and negative coefficient estimate for $Treat \times Post$ in Column (2) presents similar evidence. Our findings show that, in the context of China, banks respond to the diminished market confidence of an implicit guarantee by reducing their risk-taking behavior, confirming the dominance of the *moral hazard effect* over the *charter value effect*. Therefore, it suggests that the long-standing implicit guarantee in China contributed to the excessive risk-taking behavior of SU banks in China.

[Table 11 About Here]

7.3 Market Discipline

In the previous section, we document that SU banks become less inclined toward risk taking after Baoshang's collapse relative to SI banks. We now assess the impact of this event on market discipline. Since there are no explicit measures for market discipline, we only provide some evidence on the existence and strength of market discipline.

First, in principle, debt holders can discipline banks that engage in excessive risk taking by demanding higher issuance interest rates. Recall that the results in Tables 9 indicate that price efficiency is enhanced after the event in terms of fundamental risks for the SU banks. Focusing on the cost of NCD issuance, these results also suggest a stronger market discipline after Baoshang's collapse. Specifically, take ROA in Panel A of Table 9 as an example. The coefficient estimate for ROA in Column (1) is insignificant, denying the existence of market discipline before the event in terms of ROA. The coefficient estimate for $ROA \times Post + ROA$ is negative and significant at the 1% level (F-statistics is 35.91), implying the rise of market discipline from the perspective of ROA. Additionally, the negative coefficient estimate for $ROA \times Post$, which is statistically significant at the 1% level, suggests a stronger market discipline since the SU banks with lower ROA need to pay a

[50] The z-score is calculated as ROA plus the capital asset ratio divided by the standard deviation of ROA, which measures the distance from insolvency. A higher z-score indicates that the bank is more stable and less inclined toward risk taking. Since the z-score is highly skewed, we use the logarithm of the z-score, which is normally distributed.

higher issuance interest rate on NCDs. However, results in Column (2) show the nonexistence of market discipline with reference to ROA. In Column (3), we further confirm that stronger market discipline arises after the event for the SU banks relative to the SI banks. Similar interpretations can be applied to other bank fundamental variables in Table 9.

Second, we find direct evidence that SU banks adjust their liabilities more in reaction to tightening market discipline than the SI banks do. As predicted by Gropp, Vesala and Vulpes (2006), if stronger market discipline has indeed influenced SU banks to reduce their risk-taking behavior more after the event, we would expect a larger increase in capital and deposits and a greater decrease in risk-sensitive debt. Following Gropp, Gruendl and Guettler (2014), we test the impact of Baoshang's collapse on the capital-to-asset ratio, the non-financial deposit-to-asset ratio, and the risk-sensitive debt-to-asset ratio.

Results are reported in Table 12. In Column (1), we find that the magnitude of increase in the capital-to-asset ratio after the event is greater with SU banks relative to SI banks, but this effect is statistically insignificant. Columns (2) and (3) report a larger and statistically significant increase in the deposit-to-asset ratio and a larger and statistically significant decrease in the risk-sensitive debt-to asset ratio after Baoshang's collapse for SU banks compared with SI banks. In general, our findings suggest that debt holders' intensity of monitoring increases and market discipline becomes more stringent for SU banks following this event.

[Table 12 About Here]

7.4 Summary

In general, we find that China's long-standing implicit government guarantees distort SU banks' risk-taking incentives, impair market discipline, and erode price efficiency. When confronted with a diminished market perception of the government bailout and the resulting higher financing costs on debt issuance, SU banks decrease (increase) their reliance on risk-sensitive debt (retail deposits) for funding while also containing their risky investments to reduce the volatility of their asset returns. Additionally, our evidence indicates that the implicit guarantees boost the stock prices of SU banks.

While abandoning blind faith in government bailouts may jeopardize financial stability ex post, our findings indicate that it will improve price efficiency, mitigate moral hazard, and prevent banks from taking excessive risks, all of which contribute to ex ante efficiency and stability.

8 Robustness Check

In this section, we provide robustness checks for our main results on the causal effect of Baoshang's collapse on credit spreads on NCD issuance.

8.1 Adding Failed Issuance Samples

As mentioned in Section 5.3, our main analyses are free of NCD samples with failed issuance, which could potentially lead to selection bias. In this section, we extend our sample universe to include those failure samples and explore how this would affect our main results. We first count the success and failure observations for SU and SI banks before and after the event, respectively. During the pre-event period, there are 8,736 successful and 480 failed bank-day observations for SU banks, and 1,657 successful and 4 failed bank-day observations for SI banks. During the post-event period, there are 9,182 successful and 1,609 failed bank-day observations for SU banks, and 1,838 successful and 10 failed bank-day observations for SI banks. This suggests a huge increase in the failure samples after the event for SU banks, but issuance failure for SI banks is much more unlikely either before or after the event.

Panel A of Figure 7 plots the daily average of credit spreads including the failed samples.[51] For the successful issuance samples, the pattern of changes in credit spreads for SU and SI banks is similar to our previous findings. For the failed NCDs issued by SU banks, we find that the credit spread gap between failed and successful samples is almost zero before the event but becomes larger after the event. This also indicates that some NCDs issued by SU banks fail even with larger credit spreads. Panel B of Figure 7 shows the dynamic effect of Baoshang's collapse on credit spreads, similar to Figure 3, which also validates the parallel trend assumption.

[Figure 7 About Here]

We next conduct the DiD estimation using both successful and failed issuance samples, where the setting is the same as in Equation (9) except for replacing the control of the logarithm of the actual issuance size ($LnIssSize$) by the logarithm of the planned issuance size ($LnPIssSize$). Results in Table 13 show that the effect of Baoshang's collapse on credit

[51] The green dashed line, which represents observations of failed SI banks, is less informative as a result of few samples of failed NCDs issued by SI banks. Specifically, there are only 4 and 10 failed bank-day observations for SI banks before and after Baoshang's collapse, respectively.

spreads is even larger. In sum, adding failed NCD samples would make our main results stronger, and our baseline regression in the previous section provides a lower estimate for the impact of an implicit non-guarantee on credit spreads.

[Table 13 About Here]

8.2 Changing Sample Period

Recall that the main results in Table 2 use a sample from October 1, 2018, to December 31, 2019, in order to rule out the possible concern caused by the COVID-19 pandemic. We now examine whether these results are robust when changing the sample period. Specifically, we use a 3-month, 6-month, 9-month, and 12-month window before and after Baoshang's collapse, respectively. Table 14 shows that the coefficient estimates for $Treat \times Post$ in Columns (1)-(4) are all positive and statistically significant at the 1% level. We also find that this effect is stronger if the time window is closer to the event.

[Table 14 About Here]

8.3 Security-Level Analysis

Next, we examine whether our main results are robust at the security-day level. In our previous analyses, we only keep the NCD issuance sample with the largest issuance size if a bank issues more than one NCD on the same day because our main focus is the bank-day-level data and the security-day-level data only have one-period observations without any time variation. Nevertheless, we still keep all NCD issuance observations and reestimate Equation (9) using the security-day-level data. Results in Table 15 indicate both the qualitatively and quantitatively similar effects of Baoshang's collapse on the credit spreads on NCD issuance. Figure OA.3 plots the dynamic effect in the Online Appendix.

[Table 15 About Here]

9 Conclusion

The long-standing guarantee that applies to the entire banking system in China came to an end on May 24, 2019, with the publicly announced collapse of Baoshang Bank. Although public funds were used to bail out the majority of Baoshang's creditors, the government, for the first time in two decades, refrained from bailing out all of the bank's creditors. In this paper, we document the consequences of this small deviation from full guarantee and reflect on the impact of the long-lasting government guarantee on the Chinese banking system. We find that the massive liquidity injections and various guarantees provided to the banking system following Baoshang's collapse maintained market-wide liquidity and averted any severe financial contagion. Somewhat surprisingly, despite all of these government supports, we still observe that the Baoshang event significantly worsened the funding conditions in the interbank market, resulting in surging credit spreads and tremendous NCD issuance failures.

We conduct extensive empirical analysis to identify the underlying reason for this observation — the diminished confidence in future government bailouts of SU banks. Because of the implicit non-guarantee, Baoshang's collapse had a spillover effect on other SU banks, creating liquidity distress for some of them (e.g., Bank of Jinzhou), but it had little effect on the funding conditions of SI banks. This finding confirms the strong public belief in government bailouts that would have been extended to SU banks prior to the Baoshang event.

Our empirical setting is unique in that it enables us to examine the impact of the government guarantee on SU banks, which constitute the majority of the banking sector, are generally smaller, and are unlikely to pose a threat to systemic financial stability. We provide evidence showing that the government bailout and the anticipation of it resulted in SU banks taking on excessive risk, impairing market discipline, reducing price efficiency, but increasing bank equity prices.

Admittedly, government guarantees can be desirable. Apart from ensuring ex post financial stability, they may affect bank creditors' risk-sharing, thereby increasing overall welfare (Keister, 2016). Government guarantees may also strengthen banks' role in liquidity provision (Allen et al., 2018). From this perspective, our paper is far from a comprehensive evaluation of government bailout policies, and we remain silent on many possible channels through which government guarantees may affect the ex ante incentives of banks and creditors. These, we believe, are promising areas for future research that will shed light on both the optimal design of a bailout scheme and the regulatory reform of China's banking system.

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Tables and Figures

Panel A. Credit Spreads on NCD issuance Panel B. Failure Ratio on NCD issuance

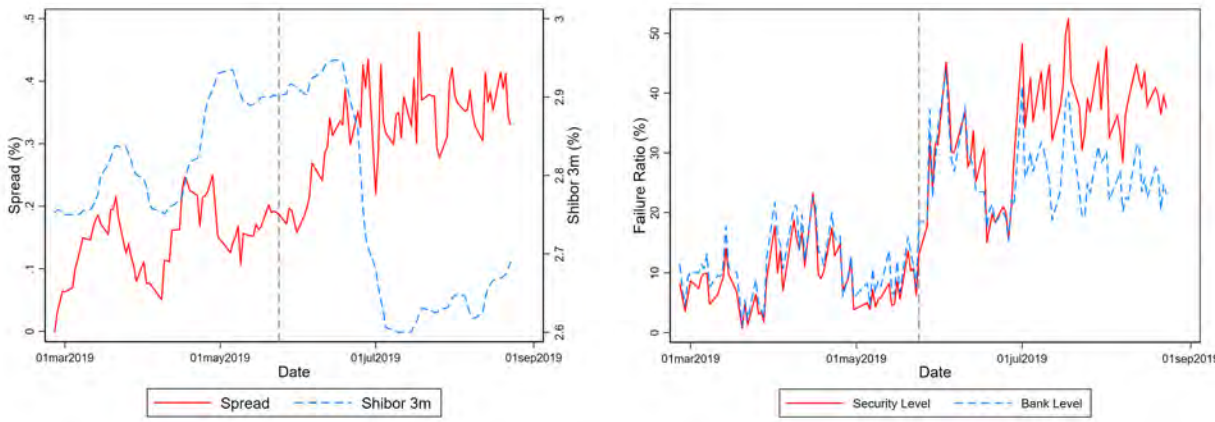

Figure 1. Market Responses after Baoshang's Collapse

Notes: This figure presents the market responses after Baoshang's collapse. The sample is from February 24, 2019, to August 24, 2019, and the event date is May 24, 2019, when Baoshang Bank was taken over. Panel A plots the three-month Shibor interest rate and the daily average credit spreads on NCDs issued by all banks. $Spread_{it}$ is the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. Panel B plots the daily failure ratio on NCD issuance. The solid red line plots the ratio of the total number of failed NCD issuance to the total number of NCD issuance in each day. The dashed blue line plots the ratio of the total number of banks issuing failed NCDs to the total number of banks issuing NCDs in each day.

Panel A. Simple Average	Panel B. Size-weighted Average

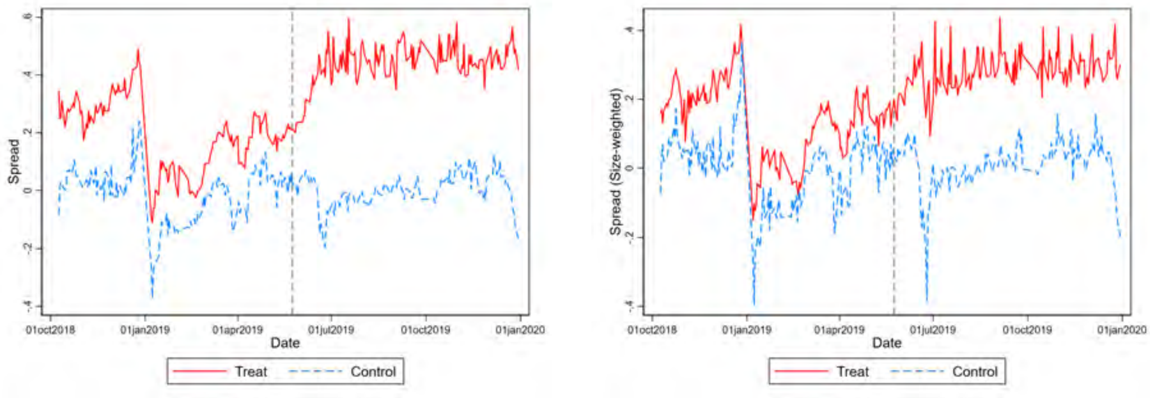

Figure 2. Daily Average Credit Spreads on NCD Issuance

Notes: This figure presents the daily average credit spreads on NCD issuance from October 1, 2018, to December 31, 2019, and the event date is May 24, 2019, when Baoshang Bank was taken over. $Spread_{it}$ is the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise. Panel A plots the simple average of credit spreads, and Panel B plots the NCD actual issuance size-weighted average of credit spreads.

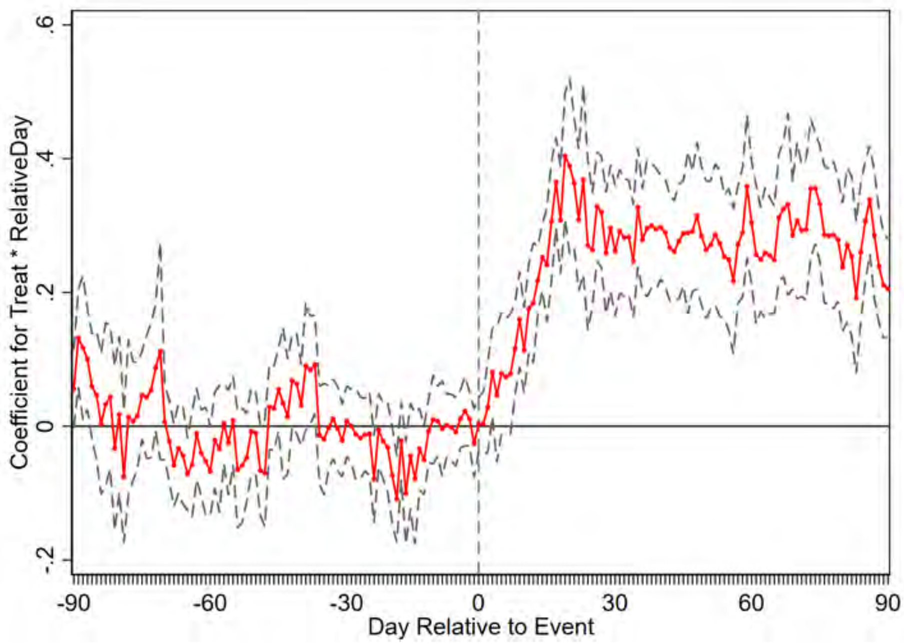

Figure 3. Dynamic Impact of Baoshang Collapse on Credit Spreads

Notes: This figure presents the dynamic impact of Baoshang's collapse on the credit spreads on NCD issuance. We consider a 90-day window before and after the event, respectively. All continuous independent variables are truncated at the 1st and 99th percentile levels. The dashed lines correspond to 95% confidence intervals, which are based on standard errors clustered at the bank level. Specifically, the x-axis shows the day relative to the event, and the y-axis plots the coefficient estimates for $Treat_i \times RelativeDay_t$ estimated from the equation

$$Spread_{it} = \alpha + \sum_{t=-90}^{90} \beta_t Treat_i \times RelativeDay_t + X_{it}\Gamma + \mu_i + \lambda_t + \epsilon_{it},$$

where $Spread_{it}$ is the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise. $RelativeDay_t$ is a dummy equal to one if the observation is on the t-th day relative to the event day. X_{it} is a vector of control variables, including the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). μ_i and λ_t are bank and day fixed effects, respectively. The point estimate immediately before the event date is normalized to zero.

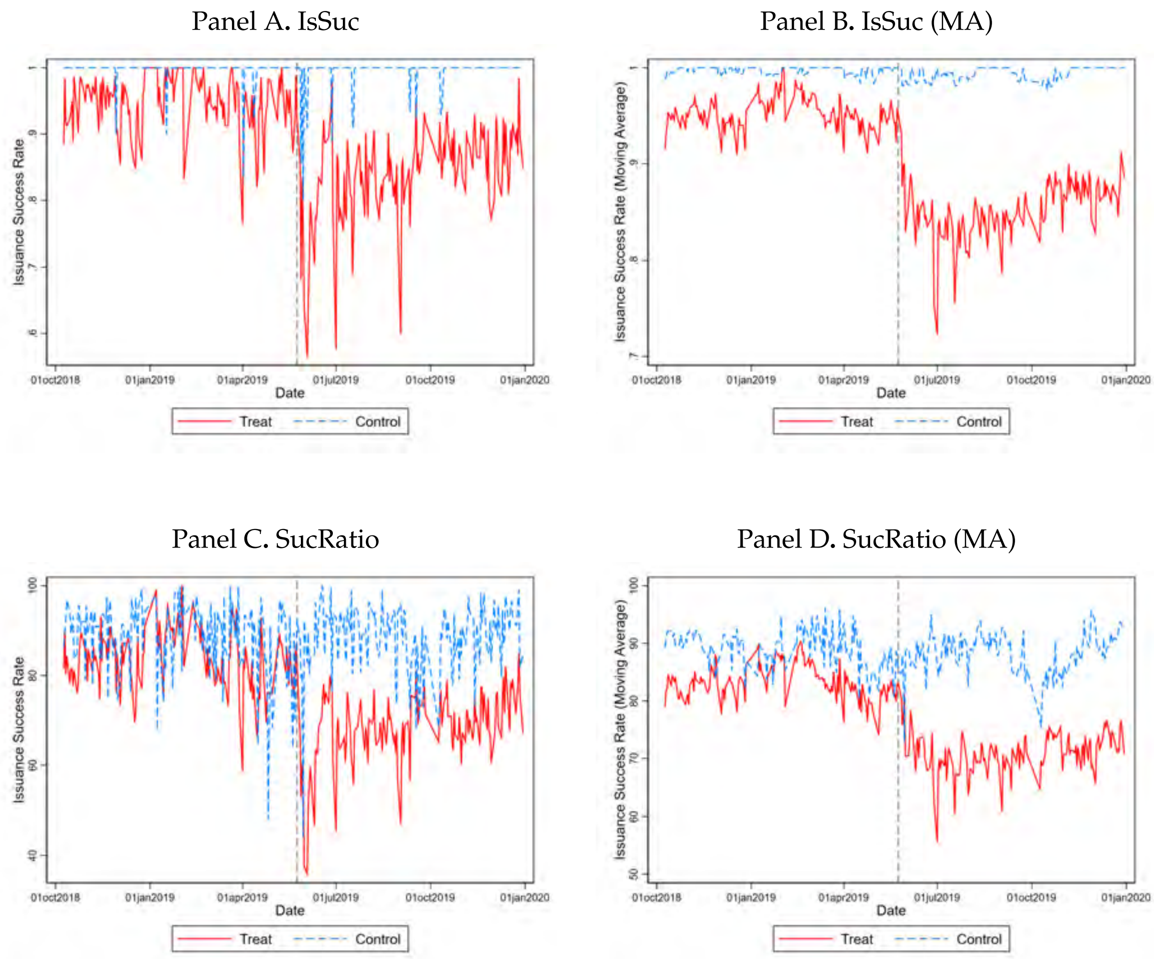

Figure 4. Daily Average Success Rate on NCD Issuance

Notes: This figure presents the daily average success rate on NCD issuance from October 1, 2018, to December 31, 2019, and the event date is May 24, 2019, when Baoshang Bank was taken over. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise. Panel A plots the daily average of $IsSuc_{it}$, which equals one if the actual issuance size of the NCD is positive and zero otherwise. Panel B plots the daily average of $IsSuc_{it}$ with a 15-day moving average window. Panel C plots the daily average of $SucRatio_{it}$, which is the ratio of the actual issuance size to the planned issuance size. Panel D plots the daily average of $SucRatio_{it}$ with a 15-day moving average window.

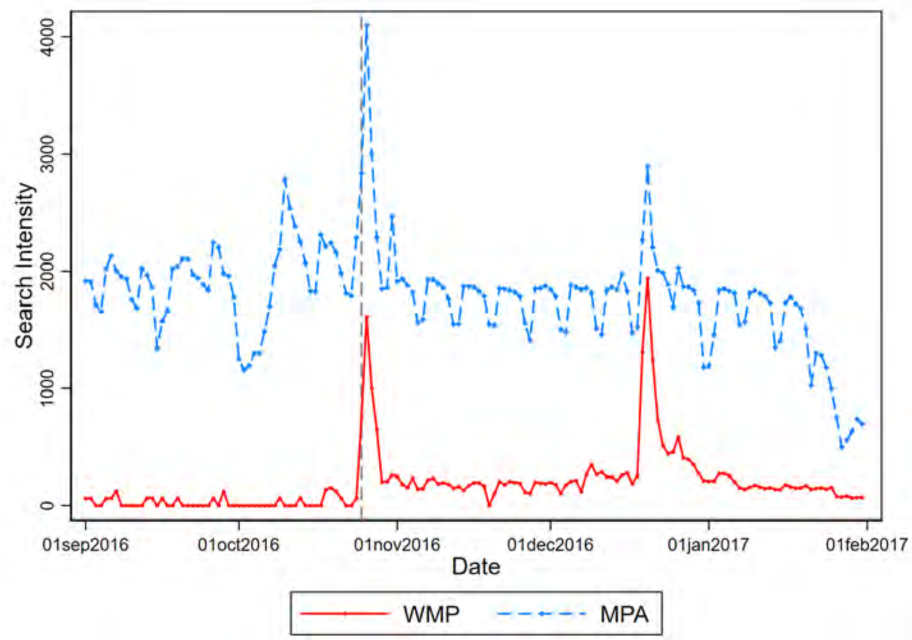

Figure 5. Search Intensity for News on Terms "WMP" and "MPA" in Chinese on Baidu

Notes: This figure presents the search intensity for news on the terms "off-balance-sheet wealth management products" and "macro prudential assessment" in Chinese on Baidu. The sample is from September 1, 2016, to January 31, 2017. The intensity of two lines both peak on October 26, 2016, and December 20, 2016.

Panel A. Credit Spreads Panel B. The Dynamic Impact

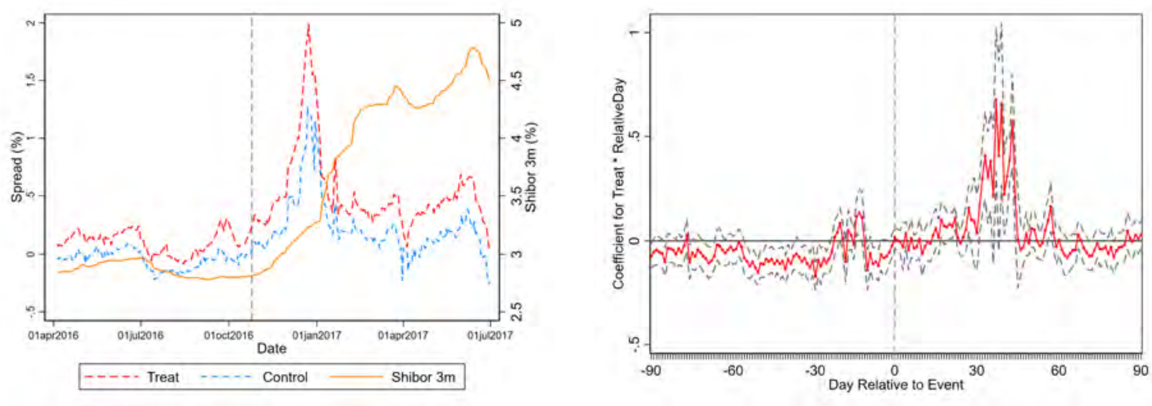

Figure 6. Placebo Test for Liquidity Shortage

Notes: This figure presents the placebo test in which the market is short of liquidity. The sample is from April 1, 2016, to June 30, 2017, and the event date is October 25, 2016, when the market anticipated banks' off-balance-sheet wealth management products to be included in the monitoring checklist under the macro prudential assessment framework. $Spread_{it}$ is the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise. All continuous independent variables are truncated at the 1st and 99th percentile levels. Panel A plots the daily average credit spreads on NCD issuance around the liquidity shock. Panel B shows the dynamic impact of the liquidity shock on the credit spreads on NCD issuance, and the setting is the same as in Equation (10).

Panel A. Credit Spreads   Panel B. The Dynamic Impact

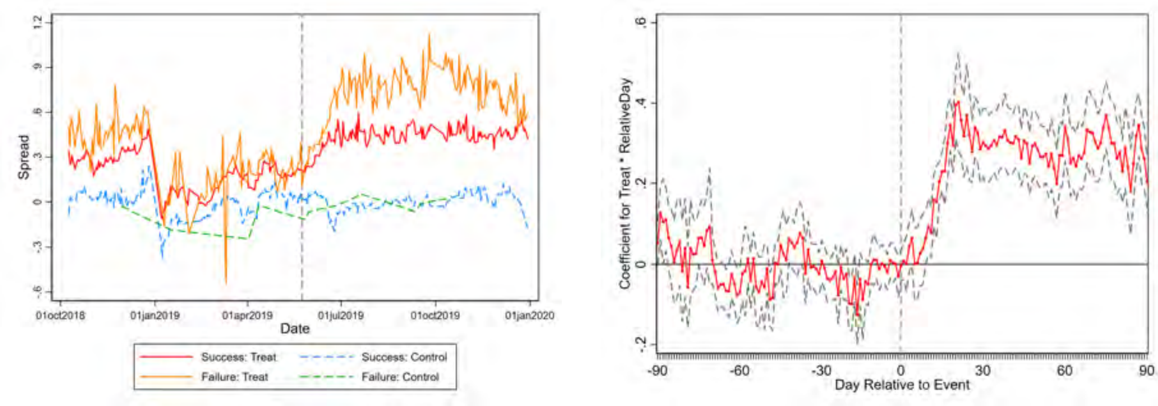

Figure 7. Robustness Check: Adding Failed Issuance Samples

Notes: This figure presents the robustness results when adding failed issuance samples. The sample consists of both successful and failed NCDs issued from April 1, 2016, to June 30, 2017. $Spread_{it}$ is the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise. All continuous independent variables are truncated at the 1st and 99th percentile levels. Panel A plots the daily average credit spreads on NCD issuance. Panel B shows the dynamic impact of Baoshang's collapse on the credit spreads on NCD issuance, and the setting is the same as in Equation (10) except for replacing the control of the logarithm of the actual issuance size by the logarithm of the planned issuance size.

Table 1. Summary Statistics

Notes: This table reports the summary statistics for the main variables. Variables are defined in Table B1 in Appendix B. The credit spreads, actual issuance size, and duration of the NCD are on a daily basis, and all other variables are on a quarterly basis. Panel A describes the summary statistics of the whole sample period from October 1, 2018, to December 31, 2019. Panel B compares the mean of the main variables between SU and SI banks during the pre-event period and reports the robust *t*-statistics in Column (4). Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Panel A. Summary Statistics of the Whole Sample

Variable	Mean	Median	SD	Min	Max	Obs
Spread (%)	0.278	0.210	0.307	-0.560	2.297	21368
IssSize (Billion RMB)	0.706	0.290	1.169	0.020	8.600	21089
Duration (Year)	0.538	0.500	0.363	0.080	1.000	21368
TotalAsset (Trillion RMB)	0.667	0.122	2.206	0.007	22.770	975
DebtAssetRatio (%)	92.001	92.211	1.512	83.810	95.092	967
ROA (%)	0.666	0.654	0.348	0.053	1.776	919
NPL (%)	1.740	1.605	0.812	0.290	6.570	770
CAR (%)	13.941	13.640	1.971	7.770	21.660	913
LiquidRatio (%)	15.850	14.963	4.610	7.809	32.275	886
TotalNCD (Billion RMB)	25.606	2.840	60.468	0.000	431.280	1547
NCDRatio (%)	8.477	7.537	6.434	0.000	24.515	976
IBAsset (Trillion RMB)	0.063	0.009	0.177	0.001	1.437	588
IBAssetRatio (%)	6.572	5.563	4.116	1.282	25.299	588
IBDebt (Trillion RMB)	0.219	0.036	0.511	0.001	2.738	652
IBDebtRatio (%)	22.368	22.780	8.844	3.643	41.038	652
HS (Million Shares)	8.797	3.000	14.803	0.100	108.500	4617
HSRatio (%)	70.091	76.923	30.340	8.929	100.000	4635
HV (Billion RMB)	0.876	0.291	1.469	0.010	10.726	4591
HVRatio (%)	69.889	76.468	30.344	8.886	100.000	4604
OfNAV (%)	13.956	10.310	11.715	1.070	63.370	4587
LnZscore	4.193	4.168	0.778	2.213	5.819	1075
Std_ROA	0.200	0.158	0.148	0.031	0.942	903
CapitalAssetRatio (%)	9.533	9.476	1.472	4.927	16.665	830
DepositRatio (%)	69.497	68.893	9.605	44.833	88.506	889
RSDebtRatio (%)	21.064	21.374	9.571	2.974	43.310	775

Panel B. Pre-Event Comparison

Variable	(1) Treat	(2) Control	(3) Diff.	(4) T-stat.
Spread (%)	0.214	-0.008	0.222***	59.04
IssSize (Billion RMB)	0.503	2.054	-1.551***	-30.02
Duration (Year)	0.524	0.596	-0.072***	-7.40
TotalAsset (Trillion RMB)	0.173	6.149	-5.976***	-5.90
DebtAssetRatio (%)	91.990	92.485	-0.494***	-4.03
ROA (%)	0.667	0.561	0.106*	1.72
NPL (%)	1.853	1.510	0.343***	5.15
CAR (%)	13.969	13.473	0.496*	1.69
LiquidRatio (%)	16.462	14.681	1.781**	2.52
TotalNCD (Billion RMB)	14.769	236.627	-221.858***	-13.63
NCDRatio (%)	8.833	7.183	1.650**	2.00
IBAsset (Trillion RMB)	0.015	0.370	-0.354***	-5.23
IBAssetRatio (%)	7.356	5.250	2.106***	4.63
IBDebt (Trillion RMB)	0.059	1.412	-1.352***	-10.04
IBDebtRatio (%)	22.764	26.929	-4.165***	-2.63
HS (Million Shares)	8.578	9.578	-1.000	-1.47
HSRatio (%)	54.449	76.364	-21.915***	-16.50
HV (Billion RMB)	0.861	0.958	-0.097	-1.42
HVRatio (%)	54.434	76.210	-21.776***	-16.37
OfNAV (%)	10.491	16.291	-5.800***	-12.21
LnZscore	4.057	5.107	-1.050***	-15.13
Std_ROA	0.227	0.065	0.162***	18.36
CapitalAssetRatio (%)	9.451	9.134	0.317**	2.27
DepositRatio (%)	70.061	60.868	9.193***	6.52
RSDebtRatio (%)	20.577	29.998	-9.421***	-6.54

Table 2. Impact of Baoshang's Collapse on Credit Spreads

Notes: This table provides the estimation results from a DiD regression in which the dependent variable, $Spread_{it}$, is the credit spreads on NCD issuance equal to the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. Control variables include the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). The sample is from October 1, 2018, to December 31, 2019. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	Spread	Spread	Spread
Treat × Post	0.219*** (0.02)	0.221*** (0.02)	0.206*** (0.02)
LnIssSize		-0.004** (0.00)	-0.004** (0.00)
LnDuration		0.067*** (0.01)	0.058*** (0.01)
LnTotalAsset			-0.318** (0.15)
DebtAssetRatio			0.034** (0.02)
Constant	0.184*** (0.01)	0.251*** (0.01)	-0.292 (1.39)
Day FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Rating FE	No	No	Yes
N	21289	18510	18109
R-squared	0.0636	0.1487	0.1578

Table 3. Impact of Baoshang's Collapse on Issuance Success Probability

Notes: This table provides the estimation results from a DiD regression in which the dependent variable is the success rate on NCD issuance. In Columns (1)-(2) of Panel A, the dependent variable, $IsSuc_{it}$, is a dummy equal to one if the actual issuance size of the NCD is positive and zero otherwise. In Columns (3)-(5) of Panel A, the dependent variables are the 5-day, 10-day, and 15-day moving average windows of $IsSuc_{it}$, respectively. In Columns (1)-(2) of Panel B, the dependent variable, $SucRatio_{it}$, is the ratio of the actual issuance size to the planned issuance size. In Columns (3)-(5) of Panel B, the dependent variables are the 5-day, 10-day, 15-day moving average windows of $SucRatio_{it}$, respectively. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. Control variables include the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). The sample is from October 1, 2018, to December 31, 2019. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Panel A Success Rate on NCD issuance					
	(1)	(2)	(3)	(4)	(5)
	IsSuc	IsSuc	IsSucMA5	IsSucMA10	IsSucMA15
Treat × Post	-0.063*** (0.01)	-0.041*** (0.01)	-0.050*** (0.01)	-0.050*** (0.01)	-0.048*** (0.01)
LnPIssSize		-0.002 (0.00)	-0.001 (0.00)	-0.001 (0.00)	-0.000 (0.00)
LnDuration		-0.009** (0.00)	-0.001 (0.00)	0.001 (0.00)	0.002 (0.00)
LnTotalAsset		0.175 (0.11)	0.191* (0.11)	0.193* (0.11)	0.209* (0.12)
DebtAssetRatio		0.001 (0.01)	-0.004 (0.01)	-0.004 (0.01)	-0.004 (0.01)
Constant	0.939*** (0.00)	-0.519 (1.43)	-0.226 (1.39)	-0.262 (1.39)	-0.349 (1.40)
Day FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes	Yes
N	23439	20360	20238	20074	19867
R-squared	0.0022	0.0028	0.0081	0.0131	0.0172

Panel B Success Ratio on NCD issuance					
	(1)	(2)	(3)	(4)	(5)
	SucRatio	SucRatio	SucRatioMA5	SucRatioMA10	SucRatioMA15
Treat × Post	-10.341*** (1.73)	-8.209*** (2.08)	-8.759*** (1.99)	-7.422*** (1.94)	-6.985*** (1.94)
LnPIssSize		0.758 (0.65)	-0.281 (0.29)	-0.348 (0.22)	-0.280 (0.21)
LnDuration		-1.032** (0.50)	-0.368 (0.31)	-0.057 (0.27)	0.113 (0.24)
LnTotalAsset		8.985 (13.01)	11.226 (12.89)	15.798 (12.63)	15.897 (13.29)
DebtAssetRatio		0.407 (1.56)	-0.197 (1.54)	-0.665 (1.46)	-0.821 (1.43)
Constant	82.494*** (0.79)	-29.770 (144.73)	9.727 (143.73)	16.897 (132.27)	30.102 (131.91)
Day FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes	Yes
N	23439	20360	19031	19912	19703
R-squared	0.0045	0.0047	0.0118	0.0141	0.0161

Table 4. Impact of Baoshang's Collapse on Mutual Fund Holdings

Notes: This table presents the estimation results from a DiD regression in which the dependent variable is the mutual fund holdings of NCDs. In Column (1), $LnHV_{sjt}$ is the logarithm of the total holding values of NCDs issued by SU ($s = U$) or SI ($s = I$) banks for fund j. In Column (2), $HVRatio_{sjt}$ is the ratio of the total holding values of NCDs issued by SU ($s = U$) or SI ($s = I$) banks to the fund j's total holding values of NCDs. In Column (3), $OfNAV_{sjt}$ is the ratio of the total holding values of NCDs issued by SU ($s = U$) or SI ($s = I$) banks to the fund j's net asset value. The sample is from 2018Q4 to 2019Q4. All continuous variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the treatment-fund level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	LnHV	HVRatio	OfNAV
Treat × Post	-0.270***	-12.288***	-2.116***
	(0.06)	(1.82)	(0.59)
Constant	10.351***	70.222***	14.580***
	(0.02)	(0.60)	(0.20)
Quarter FE	Yes	Yes	Yes
Treat FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	4291	4301	4290
R-squared	0.0099	0.0168	0.0041

Table 5. Impact of Baoshang's Collapse on Bank Fundamentals

Notes: This table provides the estimation results from a DiD regression in which the dependent variables are proxies for bank fundamentals. In Column (1), ROA_{it} is the return on assets ratio. In Column (2), NPL_{it} is the non-performing loan ratio. In Column (3), CAR_{it} is the capital adequacy ratio. In Column (4), $LiquidRatio_{it}$ is the ratio of liquid assets to total assets. $Treat_i$ is a dummy equal to one if the type of bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event date and zero otherwise. Control variables include the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). The sample is from 2018Q4 to 2019Q4. All continuous variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
	ROA	NPL	CAR	LiquidRatio
Treat × Post	-0.012	-0.011	0.041	-1.631***
	(0.02)	(0.04)	(0.11)	(0.58)
LnTotalAsset	0.372**	-0.866	3.556***	7.926***
	(0.18)	(0.55)	(0.69)	(2.90)
DebtAssetRatio	-0.064***	0.036	-0.934***	0.454
	(0.02)	(0.07)	(0.07)	(0.28)
Constant	3.751***	4.942	73.278***	-84.466***
	(1.44)	(3.65)	(5.65)	(26.51)
Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
N	781	650	791	778
R-squared	0.0418	0.0165	0.2925	0.0535

Table 6. Impact of Baoshang's Collapse on Interbank Exposure

Notes: This table provides the estimation results from a DiD regression in which the dependent variables are proxies for the interbank exposure. In Column (1), $LnTotalNCD_{it}$ is the logarithm of the total size of outstanding NCDs. In Column (2), $NCDRatio_{it}$ is the ratio of the total size of outstanding NCDs to total debts. In Column (3), $LnIBBorrow_{it}$ is the logarithm of the total interbank borrowing (including interbank loans, securities sold under repurchase agreements, debt payable, and deposits made by other banks and financial institutions). In Column (4), $IBBorrowRatio_{it}$ is the ratio of the total interbank borrowing to total debts. In Column (5), $LnIBLend_{it}$ is the logarithm of the total interbank lending (including interbank loans extended to other banks, securities purchased under repurchase agreements, and deposits with other banks and financial institutions). In Column (6), $IBLendRatio_{it}$ is the ratio of the total interbank lending to total assets. $Treat_i$ is a dummy equal to one if the type of bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event date and zero otherwise. Control variables include the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). The sample is from 2018Q4 to 2019Q4. All continuous variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LnTotalNCD	NCDRatio	LnIBBorrow	IBBorrowRatio	LnIBLend	IBLendRatio
Treat × Post	-0.199*** (0.07)	-1.498*** (0.38)	-0.079*** (0.02)	-1.437*** (0.51)	-0.129** (0.06)	-0.597** (0.25)
LnTotalAsset	1.864*** (0.54)	8.543** (3.45)	1.737*** (0.26)	15.301*** (5.70)	2.532*** (0.35)	10.073*** (2.60)
DebtAssetRatio	0.027 (0.05)	0.164 (0.31)	0.020 (0.03)	0.319 (0.51)	0.007 (0.04)	0.022 (0.22)
Constant	-11.577*** (3.94)	-68.450** (27.38)	-9.229*** (2.66)	-125.747** (60.95)	-15.792*** (4.15)	-75.842** (32.29)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
N	847	851	590	585	493	489
R-squared	0.0837	0.0629	0.1990	0.0711	0.1527	0.0841

Table 7. Interaction Impact of Bank Fundamentals and Implicit Non-guarantee

Notes: This table provides the estimation results from a DiD regression in which the dependent variable, $Spread_{it}$, is the credit spreads on NCD issuance equal to the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if the type of bank i is systemically unimportant as certified by the PBOC and zero otherwise, $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. $High_i$ is a dummy equal to one if bank i's fundamental variable is above the median at the end of 2018 and zero otherwise, where the fundamental variable is the return on assets ratio (ROA_{it}) in Columns (1)-(2), the non-performing loan ratio (NPL_{it}) in Columns (3)-(4), and the capital adequacy ratio (CAR_{it}) in Columns (5)-(6), respectively. Control variables include the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). The sample is from October 1, 2018, to December 31, 2019. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

High	ROA		NPL		CAR	
	(1)	(2)	(3)	(4)	(5)	(6)
	Spread	Spread	Spread	Spread	Spread	Spread
High × Post	-0.132***	0.009	0.120***	0.001	-0.064**	-0.012
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
High × Post × Treat		-0.137***		0.138***		-0.080**
		(0.03)		(0.03)		(0.03)
Treat × Post		0.258***		0.141***		0.236***
		(0.03)		(0.02)		(0.02)
LnIssSize	-0.005**	-0.002	-0.005***	-0.002	-0.007***	-0.003*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnDuration	0.058***	0.059***	0.056***	0.056***	0.057***	0.058***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LnTotalAsset	-0.441***	-0.270*	-0.428**	-0.192	-0.549***	-0.354**
	(0.16)	(0.15)	(0.17)	(0.16)	(0.16)	(0.15)
DebtAssetRatio	0.057***	0.038**	0.049***	0.025	0.058***	0.037**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-1.360	-1.043	-0.764	-0.535	-0.547	-0.340
	(1.46)	(1.40)	(1.57)	(1.48)	(1.48)	(1.34)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
N	18239	18239	17716	17716	18109	18109
R-squared	0.1333	0.1804	0.1236	0.1841	0.0982	0.1633

Table 8. Impact of Baoshang's Collapse: Further Controlling Fundamentals

Notes: This table provides the estimation results from a DiD regression in which the dependent variable, $Spread_{it}$, is the credit spreads on NCD issuance equal to the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. Control variables include the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), the credit rating ($Rating_{it}$), the return on assets ratio (ROA_{it}), the non-performing loan ratio (NPL_{it}), the capital adequacy ratio (CAR_{it}), and the ratio of liquid assets to total assets ($LiquidRatio_{it}$). The sample is from October 1, 2018, to December 31, 2019. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Spread	Spread	Spread	Spread	Spread	Spread
Treat × Post	0.206***	0.198***	0.197***	0.205***	0.203***	0.185***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
LnIssSize	-0.004**	-0.004*	-0.004*	-0.004**	-0.004*	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnDuration	0.058***	0.058***	0.058***	0.058***	0.058***	0.057***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LnTotalAsset	-0.318**	-0.238	-0.371**	-0.288*	-0.308*	-0.273
	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)
DebtAssetRatio	0.034**	0.018	0.037**	0.032	0.035**	0.032
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ROA		-0.137***				-0.138***
		(0.03)				(0.04)
NPL			0.042			0.036
			(0.03)			(0.03)
CAR				0.000		0.007
				(0.01)		(0.02)
LiquidRatio					-0.003	-0.005***
					(0.00)	(0.00)
Constant	-0.292	0.608	-0.241	-0.356	-0.489	-0.470
	(1.39)	(1.43)	(1.45)	(1.73)	(1.45)	(1.94)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
N	18510	18109	17681	18270	18156	17046
R-squared	0.1487	0.1578	0.1519	0.1475	0.1516	0.1634

Table 9. Price Efficiency: Fundamental Risks

Notes: This table tests the price efficiency through fundamental risks. The dependent variable, $Spread_{it}$, is the credit spreads on NCD issuance equal to the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. Control variables include the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). In Panel A, the fundamental risks are the return on assets ratio (ROA_{it}) and the non-performing loan ratio (NPL_{it}). In Panel B, the fundamental risks are the capital adequacy ratio (CAR_{it}) and the ratio of liquid assets to total assets ($LiquidRatio_{it}$). In Columns (1) and (4) of each panel, only systemically unimportant banks are included. In Columns (2) and (5) of each panel, only systemically important banks are included. In Columns (3) and (6) of each panel, all samples are included. The sample is from October 1, 2018, to December 31, 2019. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Panel A. ROA and NPL

PE	ROA			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment	Control	Whole	Treatment	Control	Whole
PE × Post	-0.277***	0.021	-0.008	0.114***	-0.008	0.013
	(0.05)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)
Treat × Post × PE			-0.269***			0.103***
			(0.04)			(0.03)
Treat × Post			0.369***			0.026
			(0.03)			(0.05)
Treat × PE			0.077***			0.080
			(0.03)			(0.12)
PE	-0.047	-0.017	-0.115***	-0.008	-0.004	-0.084
	(0.04)	(0.05)	(0.03)	(0.03)	(0.05)	(0.11)
LnIssSize	-0.006**	0.007***	-0.002	-0.006**	0.007***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnDuration	0.069***	0.016**	0.059***	0.069***	0.016**	0.060***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LnTotalAsset	-0.117	-0.163	-0.113	-0.210	-0.171	-0.172
	(0.18)	(0.16)	(0.16)	(0.17)	(0.16)	(0.15)
DebtAssetRatio	0.010	-0.016*	0.010	0.034*	-0.017*	0.030*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Constant	0.477	3.254	0.265	-1.228	3.366	-1.099
	(1.46)	(2.06)	(1.42)	(1.47)	(2.17)	(1.42)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
N	15058	3051	18109	14630	3051	17681
R-squared	0.1576	0.0419	0.1932	0.1611	0.0418	0.1940

Panel B. CAR and Liquidity Ratio

PE	CAR			LiquidRatio		
	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment	Control	Whole	Treatment	Control	Whole
PE × Post	-0.032***	-0.004	-0.004	-0.007**	0.002	-0.000
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Treat × Post × PE			-0.028***			-0.007*
			(0.01)			(0.00)
Treat × Post			0.592***			0.315***
			(0.13)			(0.06)
Treat × PE			0.005			-0.004
			(0.02)			(0.00)
PE	0.019	0.006	0.012	-0.002	-0.002	0.002
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
LnIssSize	-0.008***	0.007***	-0.003	-0.008***	0.007***	-0.004*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnDuration	0.068***	0.016**	0.058***	0.068***	0.016**	0.058***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LnTotalAsset	-0.364**	-0.147	-0.322**	-0.323*	-0.183	-0.283*
	(0.18)	(0.15)	(0.16)	(0.18)	(0.17)	(0.16)
DebtAssetRatio	0.039*	-0.008	0.034*	0.038*	-0.017*	0.033*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Constant	-0.510	2.258	-0.505	-0.551	3.562	-0.457
	(1.72)	(1.86)	(1.61)	(1.56)	(2.28)	(1.50)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
N	15219	3051	18270	15105	3051	18156
R-squared	0.1314	0.0426	0.1685	0.1205	0.0451	0.1597

Table 10. Stock Market Response to Baoshang's Collapse

Notes: This table provides the event study results of Baoshang's collapse on May 24, 2019. The sample includes all bank stocks listed on the Chinese A-share stock market within the event window. The estimation window is [-160, -41] with a minimum observation of 30, and the event windows are [-1, +1], [-5, +5], [-10, +10], [-20,20], and [-30, +30], respectively. Each event window requires a minimum of three observations. Panel A and Panel B show the cumulative abnormal return, standardized cumulative abnormal return, and number of listed banks using the market model and market-adjusted return model, respectively. Columns (1)-(3) of each panel report the results of listed systemically unimportant banks as certified by the PBOC, and Columns (4)-(6) report the results of listed systemically important banks as certified by the PBOC. The corresponding *t*-statistics are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Panel A. Market Model						
	SU Bank			SI Bank		
	(1)	(2)	(3)	(4)	(5)	(6)
Event Window	CARet	SCARet	Bank #	CARet	SCARet	Bank #
[-1, 1]	1.660***	0.418***	13	0.258*	0.156**	17
	(2.87)	(5.38)		(1.75)	(2.05)	
[-5, 5]	-3.715***	-0.365**	13	0.805	0.279*	17
	(-2.91)	(-2.44)		(1.39)	(1.67)	
[-10, 10]	-8.641**	-0.517***	13	3.114***	0.668***	17
	(-2.51)	(-3.21)		(4.32)	(4.06)	
[-20, 20]	-7.359	-0.034	13	5.373***	0.794***	17
	(-1.31)	(-0.19)		(4.79)	(5.07)	
[-30, 30]	-14.231	-0.175	13	4.538***	0.562***	17
	(-1.58)	(-0.79)		(4.20)	(4.17)	
Panel B. Market-Adjusted Return Model						
	SU Bank			SI Bank		
	(1)	(2)	(3)	(4)	(5)	(6)
Event Window	CARet	SCARet	Bank #	CARet	SCARet	Bank #
[-1, 1]	2.251**	0.434***	13	0.242**	0.124**	17
	(2.46)	(5.73)		(1.97)	(2.11)	
[-5, 5]	-2.064*	-0.348**	13	1.288**	0.354**	17
	(-1.89)	(-2.14)		(2.27)	(2.46)	
[-10, 10]	-4.393***	-0.421***	13	2.890***	0.538***	17
	(-3.92)	(-3.17)		(4.07)	(4.04)	
[-20, 20]	-0.786	-0.013	13	6.736***	0.900***	17
	(-0.68)	(-0.11)		(5.63)	(5.76)	
[-30, 30]	-4.193**	-0.133	13	6.294***	0.692***	17
	(-2.13)	(-0.97)		(6.76)	(6.56)	

Table 11. Impact of Baoshang's Collapse on Risk Taking

Notes: This table provides the estimation results from a DiD regression in which the dependent variables are proxies for banks' risk-taking behavior. In Column (1), $LnZscore_{it}$ is the logarithm of the sum of ROA and the capital asset ratio divided by the volatility of ROA. In Column (2), Std_ROA_{it} is the volatility of ROA. $Treat_i$ is a dummy equal to one if the type of bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event date and zero otherwise. Control variables include the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). The sample is from 2018Q4 to 2019Q4. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)
	LnZscore	Std_ROA
Treat × Post	0.159***	-0.019***
	(0.05)	(0.01)
LnTotalAsset	0.352	-0.013
	(0.49)	(0.10)
DebtAssetRatio	-0.132***	0.009
	(0.04)	(0.01)
Constant	13.660***	-0.541
	(3.01)	(0.58)
Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Rating FE	Yes	Yes
N	788	779
R-squared	0.0447	0.0088

Table 12. Impact of Baoshang's Collapse on Market Discipline

Notes: This table provides the estimation results from a DiD regression in which the dependent variables are proxies for market discipline. In Column (1), $CapitalAssetRatio_{it}$ is the capital-to-asset ratio. In Column (2), $DepositRatio_{it}$ is the non-financial deposit-to-asset ratio. In Column (3), $RSDebtRatio_{it}$ is the risk-sensitive debt-to-asset ratio. $Treat_i$ is a dummy equal to one if the type of bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event date and zero otherwise. Control variables include the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), and the credit rating ($Rating_{it}$). The sample is from 2018Q4 to 2019Q4. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	CapitalAssetRatio	DepositRatio	RSDebtRatio
Treat × Post	0.019	1.125**	-1.179**
	(0.09)	(0.46)	(0.48)
LnTotalAsset	-0.985**	-16.598***	16.467**
	(0.41)	(5.95)	(6.52)
DebtAssetRatio	-0.886***	-0.289	1.146**
	(0.04)	(0.55)	(0.58)
Constant	98.593***	218.390***	-207.942***
	(3.74)	(42.98)	(42.35)
Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
N	730	780	675
R-squared	0.6124	0.1095	0.1713

Table 13. Robustness Check: Adding Failed Issuance Samples

Notes: This table provides the estimation results from a DiD regression in which the dependent variable, $Spread_{it}$, is the credit spreads on NCD issuance equal to the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. Control variables include the logarithm of the planned issuance size of the NCD ($LnPIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), the credit rating ($Rating_{it}$), the return-on-asset ratio (ROA_{it}), the non-performing loan ratio (NPL_{it}), the capital adequacy ratio (CAR_{it}), and the ratio of liquid assets to total assets ($LiquiRatio_{it}$). The sample consists of both successful and failed NCD issuance and ranges from October 1, 2018, to December 31, 2019. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	Spread	Spread	Spread
Treat × Post	0.230***	0.217***	0.194***
	(0.02)	(0.02)	(0.02)
LnPIssSize		-0.001	0.000
		(0.00)	(0.00)
LnDuration		0.065***	0.061***
		(0.01)	(0.01)
LnTotalAsset		-0.449***	-0.364**
		(0.16)	(0.17)
DebtAssetRatio		0.042**	0.035
		(0.02)	(0.03)
ROA			-0.154***
			(0.04)
NPL			0.039
			(0.03)
CAR			0.005
			(0.02)
LiquidRatio			-0.005**
			(0.00)
Constant	0.203***	-0.020	0.005
	(0.01)	(1.48)	(2.13)
Day FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Rating FE	No	Yes	Yes
N	23439	20360	18547
R-squared	0.0580	0.1564	0.1666

Table 14. Robustness Check: Changing Sample Period

Notes: This table provides the estimation results from a DiD regression in which the dependent variable, $Spread_{it}$, is the credit spreads on NCD issuance equal to the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. Control variables include the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), the credit rating ($Rating_{it}$), the return-on-asset ratio (ROA_{it}), the non-performing loan ratio (NPL_{it}), the capital adequacy ratio (CAR_{it}), and the ratio of liquid assets to total assets ($LiquiRatio_{it}$). In Column (1), the sample is from February 24, 2019, to August 24, 2019. In Column (2), the sample is from November 24, 2018, to November 24, 2019. In Column (3), the sample is from August 24, 2018, to February 24, 2020. In Column (4), the sample is from May 24, 2018, to May 24, 2020. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
	±3 months	±6 months	±9 months	±12 months
Treat × Post	0.209***	0.189***	0.169***	0.164***
	(0.02)	(0.02)	(0.02)	(0.02)
LnIssSize	0.003	-0.001	-0.002	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
LnDuration	0.061***	0.048***	0.063***	0.072***
	(0.00)	(0.00)	(0.00)	(0.00)
LnTotalAsset	-0.732**	-0.199	-0.281**	-0.462***
	(0.32)	(0.19)	(0.13)	(0.17)
DebtAssetRatio	0.035	0.032	0.022	0.019
	(0.03)	(0.02)	(0.02)	(0.02)
ROA	-0.267***	-0.167***	-0.072**	-0.027
	(0.09)	(0.04)	(0.03)	(0.03)
NPL	0.052	0.030	0.052**	0.094**
	(0.08)	(0.04)	(0.03)	(0.05)
CAR	0.001	0.002	0.006	0.013
	(0.02)	(0.02)	(0.01)	(0.01)
LiquidRatio	0.005	-0.004	-0.003*	-0.003
	(0.01)	(0.00)	(0.00)	(0.00)
Constant	2.946	-1.050	0.409	2.018
	(3.52)	(2.18)	(1.42)	(1.55)
Day FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
N	6863	13426	20088	26537
R-squared	0.2234	0.1439	0.1553	0.1529

Table 15. Robustness Check: Security-level Analysis

Notes: This table provides the estimation results from a DiD regression in which the dependent variable, $Spread_{it}$, is the credit spreads on NCD issuance equal to the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise, and $Post_t$ is a dummy equal to one if the observation is after the event day and zero otherwise. Control variables include the logarithm of the actual issuance size of the NCD ($LnIssSize_{it}$), the logarithm of the duration of the NCD ($LnDuration_{it}$), the logarithm of the total assets ($LnTotalAsset_{it}$), the debt-to-asset ratio ($DebtAssetRatio_{it}$), the credit rating ($Rating_{it}$), the return-on-asset ratio (ROA_{it}), the non-performing loan ratio (NPL_{it}), the capital adequacy ratio (CAR_{it}), and the ratio of liquid assets to total assets ($LiquiRatio_{it}$). The sample is at the security level from October 1, 2018, to December 31, 2019. All continuous independent variables are truncated at the 1st and 99th percentile levels. Robust standard errors clustering at the bank level are displayed in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	(1) Spread	(2) Spread	(3) Spread
Treat × Post	0.215*** (0.02)	0.198*** (0.02)	0.170*** (0.02)
LnIssSize		-0.002 (0.00)	-0.000 (0.00)
LnDuration		0.053*** (0.01)	0.052*** (0.01)
LnTotalAsset		-0.249 (0.17)	-0.476** (0.20)
DebtAssetRatio		0.022 (0.02)	0.042 (0.03)
ROA			-0.088* (0.05)
NPL			0.047 (0.05)
CAR			0.019 (0.02)
LiquidRatio			-0.004* (0.00)
Constant	0.166*** (0.01)	0.281 (1.52)	0.198 (2.29)
Day FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Rating FE	No	Yes	Yes
N	33959	28529	24376
R-squared	0.0700	0.1528	0.1636

Appendix A List of Systemic Important Banks

Table A1. The List of Systemically Important Banks Certified by PBOC

Notes: This table presents the list of systemically important banks released by PBOC on October 15, 2021. See the People's Bank of China, http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/4360688/index.html, for details.

Bank Name	Bank Type	Bank Nature
Ping An Bank	Joint-stock Commercial Bank	Non State-owned Enterprise
China Everbright Bank	Joint-stock Commercial Bank	Central State-owned Enterprise
Huaxia Bank	Joint-stock Commercial Bank	Local State-owned Enterprise
China Guangfa Bank	Joint-stock Commercial Bank	Central State-owned Enterprise
Bank of Ningbo	City Commercial Bank	Non State-owned Enterprise
Bank of Shanghai	City Commercial Bank	Local State-owned Enterprise
Bank of Jiangsu	City Commercial Bank	Local State-owned Enterprise
Bank of Beijing	City Commercial Bank	Local State-owned Enterprise
Shanghai Pudong Development Bank	Joint-stock Commercial Bank	Local State-owned Enterprise
China CITIC Bank	Joint-stock Commercial Bank	Central State-owned Enterprise
China Minsheng Bank	Joint-stock Commercial Bank	Non State-owned Enterprise
Postal Savings Bank of China	State-owned Commercial Bank	Central State-owned Enterprise
Bank of Communications	State-owned Commercial Bank	Central State-owned Enterprise
China Merchants Bank	Joint-stock Commercial Bank	Non State-owned Enterprise
Industrial Bank	Joint-stock Commercial Bank	Local State-owned Enterprise
Industrial and Commercial Bank of China	State-owned Commercial Bank	Central State-owned Enterprise
Bank of China	State-owned Commercial Bank	Central State-owned Enterprise
China Construction Bank	State-owned Commercial Bank	Central State-owned Enterprise
Agricultural Bank of China	State-owned Commercial Bank	Central State-owned Enterprise

Appendix B Variable Definition

Table B1. Variable Definition

Notes: This table gives the definition of the main variables.

Variable	Definition
Dependent variable	
$Spread_{it}$	The difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day issued by bank i at day t
$IsSuc_{it}$	A dummy equal to one if the actual NCD size issued by bank i at day t is positive and zero otherwise
$SucRatio_{it}$	The ratio of the actual NCD issuance size to the planned NCD issuance size for bank i at day t
Independent variable	
$Treat_i$	A dummy equal to one if the type of bank i is systemically unimportant as certified by the PBOC and zero otherwise
$Post_t$	A dummy equal to one if the observation t is after the event day and zero otherwise
Control variable	
$LnIssSize_{it}$	The logarithm of the actual issuance size of the NCD issued by bank i at day t
$LnDuration_{it}$	The logarithm of the duration of the NCD issued by bank i at day t
$LnTotalAsset_{it}$	The logarithm of bank i's total assets at quarter t
$DebtAssetRatio_{it}$	Bank i's ratio of total debts to total assets at quarter t
$Rating_{it}$	The credit rating of bank i at quarter t
Bank Fundamentals	
ROA_{it}	Bank i's return on assets ratio at quarter t
NPL_{it}	Bank i's non-performing loan ratio at quarter t
CAR_{it}	Bank i's capital adequacy ratio at quarter t
$LiquidRatio_{it}$	Bank i's ratio of liquid assets (including cash and deposit at the central bank, tradable financial assets, and deposits from the interbank market and other financial institutions) to total assets at quarter t
Interbank Exposure	
$LnTotalNCD_{it}$	The logarithm of the total size of outstanding NCDs issued by bank i at quarter t
$NCDRatio_{it}$	Bank i's ratio of total size of outstanding NCDs to total debts at quarter t
$LnIBBorrow_{it}$	The logarithm of the total interbank borrowing (including interbank loans, securities sold under repurchase agreements, debt payable, and deposits made by other banks and financial institutions) of bank i at quarter t
$IBBorrowRatio_{it}$	Bank i's ratio of the total interbank borrowing to the total debts at quarter t
$LnIBLend_{it}$	The logarithm of the total interbank lending (including interbank loans extended to other banks, securities purchased under repurchase agreements, and deposits with other banks and financial institutions) of bank i at quarter t
$IBLendRatio_{it}$	Bank i's ratio of the total interbank lending to the total assets at quarter t
Mutual Fund Holdings	
$LnHV_{ijt}$	The logarithm of the fund j's total holding values of NCDs issued by SI or SU bank i among the disclosed top 10 or top 5 holdings at quarter t
$HVRatio_{ijt}$	Fund j's ratio of total holding values of NCDs issued by SI or SU bank i to the total holding values of NCDs among the disclosed top 10 or top 5 holdings at quarter t
$OfNAV_{ijt}$	Fund j's ratio of the total holding values of NCDs issued by SI or SU bank i among the disclosed top 10 or top 5 holdings to the net asset value at quarter t
Risk-taking	
$LnZsocre_{it}$	The logarithm of the sum of ROA and capital asset ratio divided by the volatility of ROA for bank i at quarter t
Std_ROA_{it}	Bank i's volatility of ROA at quarter t calculated on an eight-quarter rolling basis with a minimum of three observations
Market Discipline	
$CapitalAssetRatio_{it}$	Bank i's ratio of capital to total assets at quarter t
$DepositRatio_{it}$	Bank i's ratio of non-financial deposits to total assets at quarter t
$RSDebtRatio_{it}$	Bank i's ratio of risk-sensitive debts (total assets minus capital minus non-financial deposits) to total assets at quarter t

Online Appendix: The Implicit non-Guarantee in the Chinese Banking System

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February 28, 2022

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I. Additional Robustness Checks

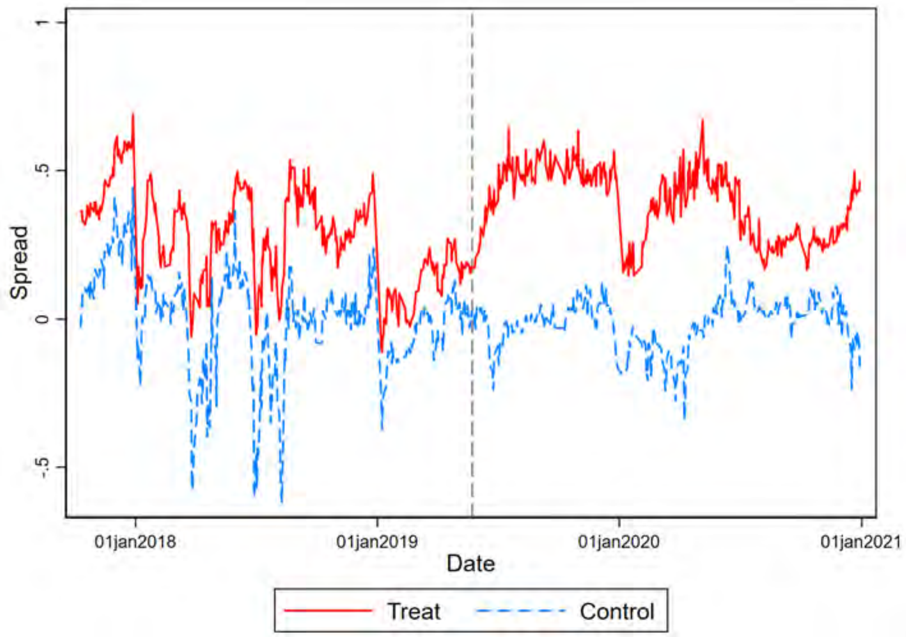
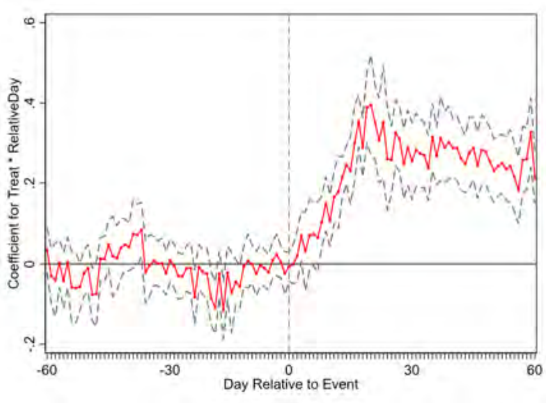


Figure OA.1. Daily Average Credit Spreads: Extending Sample Period

Notes: This figure presents the daily average credit spreads on NCD issuance from October 1, 2017, to December 31, 2020, and the event date is May 24, 2019, when Baoshang Bank was taken over. $Spread_{it}$ is the difference between the issuance interest rate on the NCD and the Shibor interest rate with the same term to maturity on the same day. $Treat_i$ is a dummy equal to one if bank i is systemically unimportant as certified by the PBOC and zero otherwise.

Panel A. 60-day Window



Panel B. 120-day Window

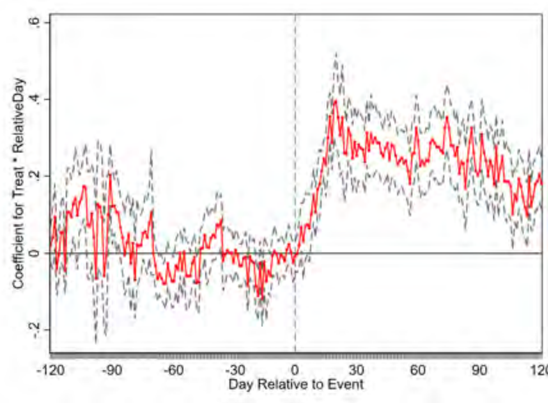


Figure OA.2. Dynamic Impact: Changing Window Lengths

Notes: This figure presents the dynamic impact of Baoshang's collapse on the credit spreads on NCD issuance with different time windows before and after the event. The setting is the same as in Equation (10) except with a 60-day window in Panel A and a 120-day window in Panel B.

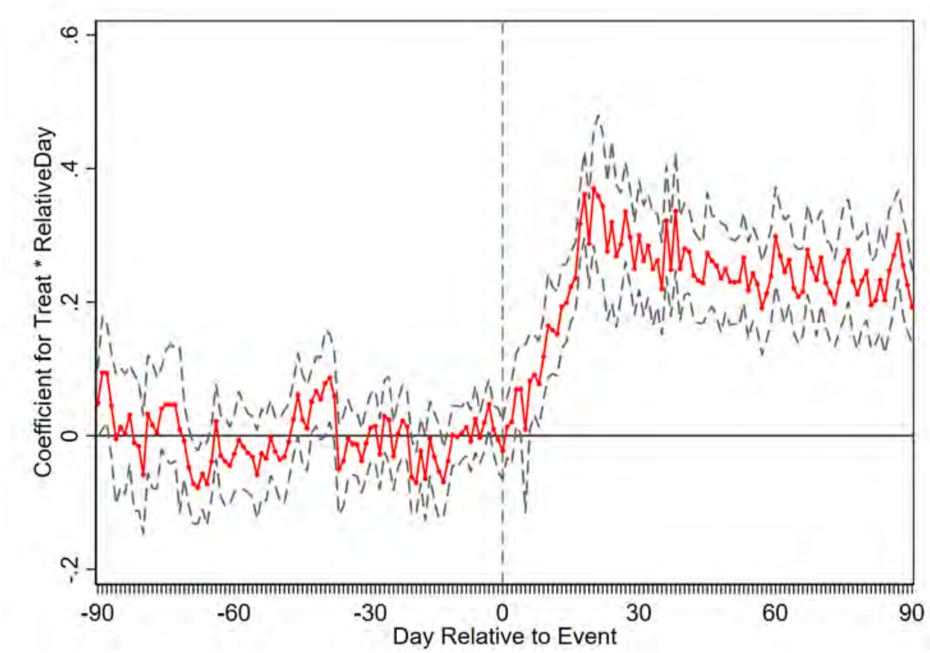


Figure OA.3. Dynamic Impact: Security-level Analysis

Notes: This figure presents the dynamic impact of Baoshang's collapse on the credit spreads on NCD issuance at the security level. The setting is the same as in Equation (10).