Wholesale Funding Runs, Spreads and Central Bank Interventions*

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Abstract

We study wholesale funding fragility using data on the Chinese market for negotiable certificates of deposit (CD) in the aftermath of a rare bank default. We document large-scale CD issuance failures despite banks offering higher yields. We further show that creditor runs are driven by relatively weak bank fundamentals, consistent with theories of dynamic debt runs. Our calibrated model suggests that emergency policy interventions are socially efficient because they reduce runs on illiquid but solvent banks.

JEL codes: E44, G14, G21, G15.
Keywords: wholesale funding fragility, bank runs, central bank intervention, implicit guarantee.

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1 Introduction

Wholesale funding markets are a major source of funding for modern banks, but dry-up episodes in Europe and the US have highlighted their fragility. The literature has proposed several potential explanations for the fragility of wholesale funding, such as adverse selection (Heider et al., 2015), asymmetric information among lenders (Pérignon et al., 2018) and standard adjustments of funding demand to higher risk premia (Afonso et al., 2011). Although understanding the actual mechanism is important for designing policy interventions, the evidence is far from conclusive. Disentangling different explanations of fragility poses several empirical challenges. Data on both realized and planned borrowing is necessary to distinguish demand- from supply-driven adjustments in the volume of wholesale funding. Information on spreads at the security or transaction level is also important in order to test the role of spreads in reflecting counterparty risk and equilibrating the market.

We study wholesale funding fragility in the Chinese market for negotiable certificates of deposit (CDs), focusing on a short but severe period of market turmoil due to the first bank failure in two decades in China. The unexpected regulatory takeover of Baoshang Bank on May 24, 2019 struck the market belief of government guarantees on interbank debts, as the authorities allowed some large creditors to bear losses.[1] This prompted investors to reassess the risks of lending to small-and-medium banks, causing a liquidity squeeze in the CD market. Three weeks after the default event, the People's Bank of China (PBC) announced targeted liquidity support and emergency backstops for small-and-medium-sized banks. Using detailed information on both successful and failed CD issues, i.e. issues that go unsubscribed at the offered yield, we document stylized facts about the market disruption and the effects of the policy response and test several hypotheses about the determinants of wholesale funding fragility.

We base our analysis on a window of 13 weeks spanning from April 22, 2019 to July 19, 2019. Following the timeline of how the Baoshang event unfolded, the event window consists three periods: (1) the relatively tranquil pre-default period, consisting of the five weeks leading up to the event, (2) the immediate aftermath of the default event, consisting of the three weeks following the event but preceding any material policy response, and (3) the post-intervention period, consisting of the five weeks after the announcement of the policy response to market turmoil. To quantify the disruption in wholesale funding at the bank level, we define a *run* as a situation where a bank experiences the failure of at least 90% of its CD issues in a week.

[1] For example, the Financial Times reported that "China's interbank market has long operated under the assumption that large debts were implicitly guaranteed by the government. But regulators have changed tack in the case of Baoshang [...]" (Weinland and Fei Ju, 2019).

We find that the default event caused significant stress in the wholesale funding market, evidenced by a sharp rise in CD issuance failures, increased yield spreads and an immediate panic among creditors. The fraction of banks experiencing a run surged from less than 2% to as high as 25%. While banks that were not affected by the disruption were on average rolling over 260% of their outstanding CDs per week, banks hit by runs were able to roll over only 10% of their outstanding CD debt.

To better understand the drivers behind this banking panic, we estimate whether the probability of issuance failures, realized spreads and the incidence of runs become more sensitive to bank characteristics such as ROA, size, book leverage and NPL ratio after the default event. Using both cross-sectional and within-bank variation in market outcomes, our analysis suggests that creditors started to differentiate between borrowers after the Baoshang default. As a result, weaker borrowers became exposed to greater rollover risk and a higher likelihood of experiencing a run. In other words, runs are not random, and are driven by weak bank fundamentals. The sensitivity of runs to bank fundamentals declined and the average run incidence fell to around 6% after the central bank stepped in to provide emergency backstop and support the CD market. Throughout the event window, market spreads adjusted by incorporating progressively more information about bank fundamentals. We also find suggestive evidence that the policy intervention had a positive effect on risk-pricing.

One interpretation of the evidence is that the surge in CD issuance failures occurred simply because offered yields had not yet adjusted to compensate investors for increased exposure to counterparty risk. We test this conjecture by estimating whether a higher offered spread reduced the probability of an issuance failure or the likelihood of a run. We find no supportive evidence. On the contrary, even when we control for bank-level unobservable characteristics, our results indicate that creditors are less likely to invest in CD issues that offer higher spreads after the event. This suggests that the equilibrium spread of CDs may be constrained by a cap above which creditors refuse to lend their funds, thus hampering market clearing in periods of turmoil.

Our empirical findings qualitatively fit several aspects of models of fundamentals-driven runs. In particular, we adapt the model of Schroth et al. (2014), which is based on the dynamic debt runs model of He and Xiong (2012), to quantitatively explore the drivers of CD runs and spreads. This model is useful in the context of CD runs because it features staggered short-term debts that are priced in a competitive market.[2] In this model, a bank

[2] The model of He and Xiong (2012) has been used to explain runs on asset-backed commercial papers. There are other important models of fundamentals-driven coordination failures, such as Rochet and Vives (2004), Goldstein and Pauzner (2005), Vives (2014) and Liu (2016). These models extend the framework of Diamond and Dybvig (1983) and allow bank fundamentals to play a role in coordination failures.

finances a long-term asset with short-term CDs, which need to be rolled over to avoid a forced liquidation. The key prediction is that a run will be triggered if the bank's fundamentals fall below an endogenous rollover threshold. The CD yield spread also depends on the distance from the rollover threshold, as creditors require to be compensated for the risk of a forced liquidation. Viewed through the lens of this model, the Baoshang event and the subsequent policy response led creditors to adopt different rollover thresholds across distinct periods in the event window. This pattern of rollover thresholds can explain the main empirical findings on CD issuance failures, runs and spreads.

Using a calibrated version of the model, we examine the scope and effectiveness of policy interventions aimed at mitigating the incidence of runs, such as liquidity provision and prudential regulation. Our analysis suggests that such policies are warranted because, even though runs are driven by poor fundamentals, many of the banks hit by runs are actually solvent. In our calibrated model, two policies are particularly effective in reducing the incidence of runs. First, by committing to provide liquidity backstops to banks in distress, the central bank can lower the rollover threshold and reduce the incidence of runs. Second, policies that lift the maximum CD yield spread at which creditors are willing to lend their funds also result in a significantly lower rollover threshold and run probability. Our calibrated model suggests similar measures undertaken by the PBC may have contributed to lowering the incidence of runs in the Chinese CD market.

Our paper contributes to different strands of the literature. The literature on China's wholesale funding market is still relatively small. Allen et al. (2017), Gu and Yun (2019) and Hachem and Song (2021) provide seminal analyses. We are the first to analyze wholesale funding fragility in Chinese markets. There is a larger literature studying the fragility of wholesale funding markets during crisis periods in the US and Europe. Our paper builds on analyses of the unsecured wholesale funding market such as Afonso et al. (2011), Heider et al. (2015), and Pérignon et al. (2018).

Our study is also related to empirical analyses of debt-runs and dynamic coordination risk in the market for asset-backed commercial papers, such as Covitz et al. (2013) and Schroth et al. (2014), and in other markets (e.g. Schmidt et al. 2016; Foley-Fisher et al. 2020; Wei and Yue 2020; Brancati and Macchiavelli 2020). Pérignon et al. (2018) and Schroth et al. (2014) are the most closely related to our paper. Pérignon et al. (2018) use data on CDs from the European market and find that funding dry-ups predict lower future bank performance. This is consistent with models where some lenders are privately informed about bank quality. In our data, wholesale funding dry-ups and spreads are explained by publicly-observable bank characteristics. A key difference between our setting and Pérignon et al. (2018) is that we study a market-wide disruption, and in Pérignon et al. (2018) dry-ups are bank-specific and driven by news about counterparty risk. Schroth et al. (2014) use data on commercial paper programs in the US during the financial crisis of 2007-2008 to estimate a structural model of dynamic debt runs. Our contribution is to substantiate the same model can successfully explain the dynamics of a different short-term debt market.

Finally, our paper contributes to the literature on on market participants' incentives to identify risk in banks (e.g. Hannan and Hanweck (1988); Flannery and Sorescu (1996); Huang and Ratnovski (2011)). There is a burgeoning literature on the effect of government guarantees on financial markets in China (e.g. Allen et al. (2018), Geng and Pan (2019), Jin et al. (2022) and Wang and Wu (2023)). This line of literature stresses the benefits of removing public guarantees in non-bank sector in terms of price efficiency and market discipline, while we show that the sudden break of an implicit guarantee can trigger runs on the banks and policy interventions are warranted to mitigate the disruptions.

2 The Chinese market for certificates of deposits

Before describing the default event, we provide a brief summary of the institutional setting of the Chinese market for CDs, including the format of CD public offerings which is important to our study.

2.1 CDs and the wholesale funding market

CDs are a money market instrument issued by deposit-taking financial institutions (banks), as a source of *unsecured* wholesale funding with growing importance in China. CDs issued by Chinese banks have a maturity of one month to one year. They are transferable and can be used as collateral by banks for repo transactions. The relative size of the Chinese CD market is comparable to the European market where banks are very reliant on wholesale funding. CD funding as a share of banks' total liabilities in China's banking sector is 5%, and this share is 15% for banks that frequently borrow through CDs between 2017 and 2020 (Figure 1a). As of end-2020, the CD market is on an equal footing with the interbank loan market (Figure 1b) and the *secured* wholesale funding from the central bank (Figure 1c), which includes liquidity obtained through the People's Bank of China (PBC)'s various lending/refinancing facilities.[3] Because of CDs' bond-like feature and the integral

[3]The interbank loan market refers to the market on which Chinese banks traditionally borrow and take deposits among each other. The *secured* wholesale funding from the central bank refers to liquidity obtained through repurchase agreements with the PBC, which includes the PBC's various lending/refinancing facilities such as the Standing Lending Facility (SLF), the Medium-term Lending Facility (MLF) as well as Open-market Operations (OMO).

role in financing and trading in China's interbank market, CDs are often compared with and subsumed in bond trading and debt financing statistics. From this perspective, the growth of the CD market significantly outpaced the growth of other types of debt instruments issued by commercial banks, which mainly include bank-issued general financial bonds, subordinate bonds, notes and hybrid capital bonds (Figure 1d).[4]

2.2 Failed and successful issuance of CDs

Almost all CD issuance in China is *quotation-based*.[5] This means two important things in our study. The first is that *before* the public offering, the issuer (i.e. the bank) determines all the *issuance terms* of CDs, including most importantly, the planned issuance amount, face value, issuance price, maturity, and offered yield. All issues are zero-coupon discount instruments paying face value at maturity, therefore the last element, the offered yield, will become the issuance yield after a successful issuance (these issuance yields are annualized yields).[6]

Once the public offering starts, investors can subscribe to a quote with the corresponding *issuance terms* set out by the issuer.[7] This process leads to the second important implication for our study, which is that under the *quotation-based* offering, a CD issue could *fail* if it goes under-subscribed. A CD issue is considered as failed if the final subscription is far below a lower bound of the planned amount.[8]

Last but not the least, banks in China follow a set issuance schedule each year, which is approved by the PBC at the beginning of the year. This means that a bank has a predetermined size and flow of CD funding. Even if market condition turns tight, banks still have to rollover CD debt and fulfill their funding need (since there is essentially no cost of trying to borrow after the issuance application is granted by the PBC). A single CD issue is at least RMB 50 million, and the maximum total issuance amount for the year is capped by

[4]Although CDs are deposit-like funding, CDs are categorized separately from the general deposit taken in banks' accounting book, and are instead classified as "bonds payable".

[5]Based on the "Rules for Issuing CDs in the Interbank Market" published by the National Interbank Funding Center (hereafter the "Rules"), the public offering of CDs can be in the format of issuance by bidding or issuance by quotation. However, in practice, almost all CD issuance is quotation-based.

[6]Offered yield = issuance yield = (face value - issuance price)/issuance price$\times$ A/T, where A is the number of days from the interest date to the same day next year, T refers to the days between the interest date to the maturity date. The face value is always RMB 100, and the issuance price is most likely below 100, similar to a zero coupon bond.

[7]This is different from an issuance by bidding where the bid-winning investor subscribes to CDs at the bid-winning price and the amount of the bid.

[8]The definition of failed issues is according to the "Rules". Although the exact threshold of the lower bound is not written in the "Rules", however, based on anecdotal evidence and our research this should be a severe under-subscription by at least half of the planned amount.

an annual quota linked to a bank-specific interbank debt exposure.[9]

2.3 Pricing of CDs

CDs are priced against the Shanghai Interbank Offered Rate (Shibor), which is an average of uncollaterized wholesale funding rates offered by a group of highly-rated Chinese banks in the interbank market. The spread between CD yields and the Shibor serves as an important barometer for the short-term wholesale market liquidity condition in China. Thus, we measure the yield spread of a CD issue as the spread between the CD offered yield and the same-maturity Shibor rate.

3 A rare bank failure and policy intervention

3.1 Regulatory takeover of Baoshang Bank

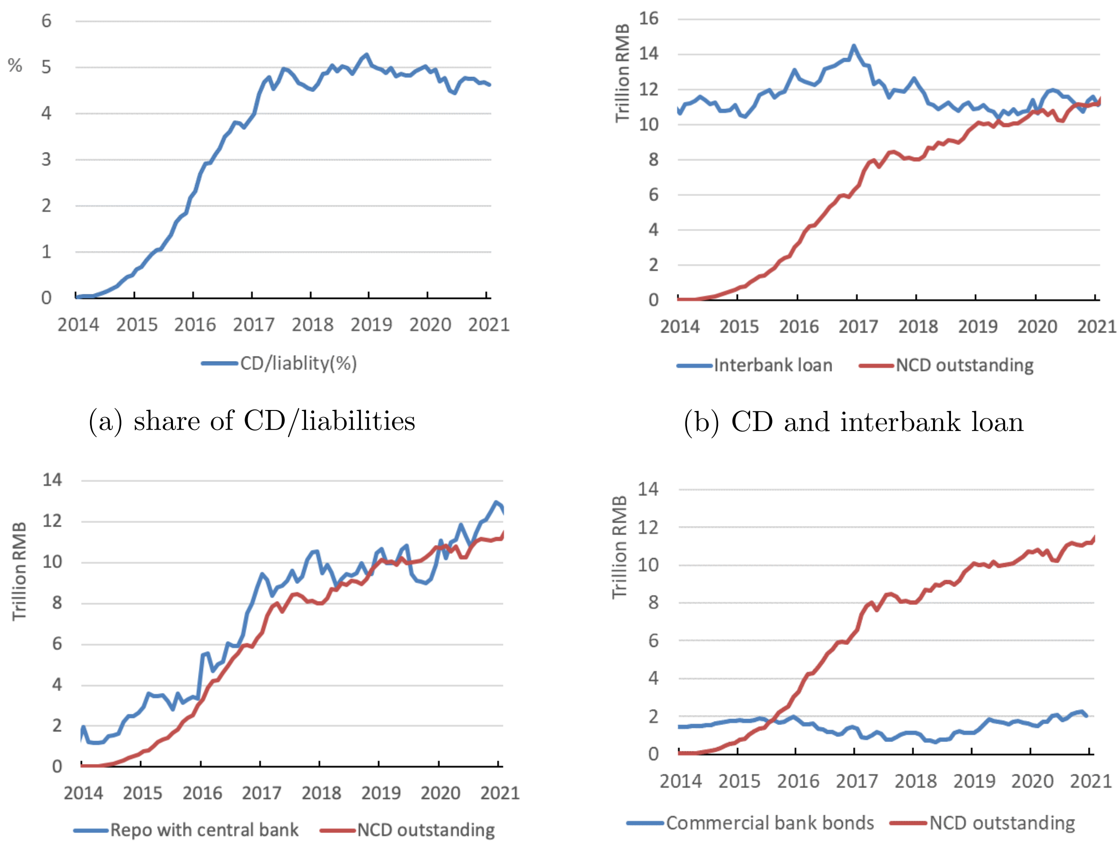
To study wholesale funding fragility, we focus on a period of turmoil in China's CD market following the sudden regulatory takeover of Baoshang Bank in the mid of 2019 - the first bank failure in China in twenty years. Baoshang Bank was a regional bank based in the Chinese province of Inner-Mongolia. In 2017, Baoshang's annual financial statement reported a non-performing loan ratio of just 1.68 percent. However, on May 24, 2019 Baoshang was taken over by the government because of its serious credit risk, the first such intervention in almost two decades.[10] The government explicitly extended guarantees on Baoshang's interbank debt, but only up to RMB 50 million per lender. This has widely been interpreted as a break of the implicit guarantee on payments in the interbank market. For example, Bloomberg News reported that "when it took control of Baoshang Bank Co. on May 24 and imposed losses on some creditors, China's government upended the long-held assumption that it would always provide banks with a 100% backstop" (Bloomberg News, 2019). Anecdotal evidence suggests the government takeover of Baoshang resulted in a liquidity squeeze for banks in China as large institutions became unwilling to lend to smaller ones, see for example Weinland (2019).[11]

[9]The CD issuance application for the current year would be rejected if the bank's interbank borrowings plus the requested amount of issuance quota exceed one-third of its total liabilities (not before 2017), under the PBC's macroprudential assessment (MPA) framework to prevent regulatory arbitrage among banks and contain systemic risk in the banking sector.

[10]A year later, in the summer of 2020, China's central bank announced the liquidation of Baoshang Bank.

[11]Two other banks defaulted later in the year in July and August, but the market reaction was not as strong as in the case of the default by Baoshang Bank.

Figure 1: Size of the CD market



(a) share of CD/liabilities

(b) CD and interbank loan

(c) CDs and repos with PBC

(d) CDs and financial bonds

Note:

1. Outstanding CDs refers to the total amount of CDs at the end of each month under the custody of Shanghai Clearing Housing (SHCH), which serves as the central depository for Negotiable CDs traded in China's interbank market.
2. Repos with central bank include liquidity obtained from the PBC's various lending facilities such as SLF, MLF as well as re-financing and OMO. Interbank loans include interbank borrowing through pledged repurchase and deposits taken among banks.
3. Bonds outstanding refers to the total amount of financial bonds issued by commercial banks outstanding at the end of each month. Financial bonds here include bank-issued general financial bonds, subordinate bonds, notes and capital bonds.
4. Data source: "Balance sheet of financial institutions" monthly report, PBC and SHCH.

3.2 Policy response to market stress

Despite the heavy blow the event took on the liquidity condition of the Chinese banking sector, the regulators did not respond through unusually large-scale liquidity support in the immediate aftermath of the event. While the PBC's net liquidity injection did increase around the event date, our computations suggest that the liquidity injection was comparable to those regularly undertaken by the central bank to counter liquidity shortages in a typical tax season or holiday season. In other words, we find no signs of precautionary liquidity injection to the interbank market before the takeover, nor any liquidity support right after the event. The PBC did not step up any targeted support for small-and-medium banks' wholesale funding debt until almost three weeks after the announcement of Baoshang Bank's default.

On Friday June 14, 2019 (at the end of the 3rd week post-takeover), the PBC announced liquidity support and emergency backstop for small-and-medium-sized banks. Specifically, the PBC expanded the size of its discount facility, which enables banks to obtain funding from the PBC in exchange for loans that they have extended to customers, typically small businesses, by RMB 200 billion. Moreover, the PBC expanded a standing loan facility (SLF), which provides banks with access to emergency liquidity, by RMB 100 billion and explicitly incorporated interbank CDs into the SLF collateral. Last but not the least, the PBC provided credit enhancements for small-and-medium-sized banks on interbank CD issuance, as a form of insurance that compensates investors if the issuer of the underlying asset defaults. This was done through private-firm bond-issuance facilities and provisions of additional funding to a prominent issuer of credit risk mitigation instruments.

3.3 Event window

We base our analysis on an event window of 13 weeks surrounding the default of Baoshang Bank, spanning from April 22, 2019 to July 19, 2019 (week 16 to week 28 in 2019). We follow the timeline of how the Baoshang event unfolded and separate the full event window into three periods:

- *Period 1 (week 16-20)*: the five weeks leading up to the event spanning from April 22, 2019 to May 24, 2019, and note that the announcement of the takeover occurred on a Friday in week 20 (May 24, 2019);

- *Period 2 (week 21-23)*: the three weeks in the immediate aftermath of the default but before any material policy response, from May 27, 2019 to June 14, 2019;

- *Period 3 (week 24-28)*: the five weeks following the regulators emergency liquidity provision announcement, from June 17, 2019 to July 19, 2019.

By comparing market dynamics across periods, we can better understand market fragility as well as how it interacts with regulators' intervention after a default event shock.[12]

[12] Our choice of the sample period also rules out effects from other small bank failures that occurred in the following months, namely the default of Bank of Jinzhou on 26 July and of Hengfeng Bank on 10 August.

4 Data

4.1 Sample

Our security-level RMB-denominated CD issuance data is from Wind Information Co. (Wind), a leading Chinese financial terminal. The dataset consolidates various sources published by China Foreign Exchange Trading System and National Interbank Funding Center. Our issuance data contains the complete *issuance terms* required by the regulator for both successful and failed CD issues, namely the issuer's name, issuance date, maturity, offered yield, the amount of issuance, and the issuer's credit rating at the time of issuance by domestic rating agencies. In the case of a failed issue, zero issuance amount is realized. Our bank-level characteristics are taken from banks' annual financial reports, which are also retrieved from Wind.

We use a sample of relatively frequent borrowers in the CD market to minimize the possibility that the observed data may pick up random or noisy borrowing behaviors. We exclude infrequent borrowers that only borrow from the CD market for a total of less than 10 calendar weeks in 2019 (on average banks issued CDs in 16 (17) out of 52 weeks in 2018 (2019)).[13] We drop foreign-owned banks, village banks, banks with missing key financial variables, and banks that did not attempt to issue any CD during the 13-week event window. Since our focus is on the wholesale market frictions and the 4 largest state-owned banks in China are very different in size and nature from the rest, we do not include them in our econometric analysis. Our final sample includes 187 frequent borrowers. Among them, there are 11 medium-sized joint-stock commercial banks, 103 city commercial banks and 73 rural commercial banks. Table 1 summarizes the composition of our sample in terms of different bank sizes and their corresponding CD market share. Here state-owned banks are included for comparison purpose. The table shows that small-and-medium-sized banks have much higher reliance on the CD market than large banks and they are also the ones that experienced more issuance failures and were more exposed to runs (which we will define in the next section).

We summarize bank and security characteristics in Table 2. Panel A shows that the majority of bank funding in our sample comes from deposits of the corporate sector and the household sector, while CDs also contribute to a sizable share of total liabilities, about 11% on average. There is a large degree of variation in bank asset size, profitability, asset quality and credit rating. An average issuer has a rating of AA+. Banks in our sample are frequent borrowers in the CD market, issuing CDs in 28 out of 52 weeks in 2018. An average bank

[13] A stricter definition of frequent borrowers is also plausible but there is a trade-off between total observations and the desired level of borrowing frequency.

Table 1: Composition of CD issuers by asset size

	Issues		Failed issues		Runs	Average asset size
	# Issuers	% Amount issued	# Issuers	% Amount failed	# Issuers	(RMB bn)
All	187	100.0	71	100.0	37	1318.0
JSCB	11	38.2	5	1.1	1	4962.0
CCB	103	39.9	57	88.1	25	378.1
RCB	73	11.8	21	10.8	11	208.2
SB	4	10.1	1	0.04	0	20233.1

Notes: (1) Sample includes all frequent issuers' CD issues and fails from April 22, 2019 to July 15, 2019. SB = State-owned banks, JSCB = Joint-stock commercial banks, CCB = City commercial banks and RCB = Rural commercial banks. (2) Asset size is based on total assets from the financial statements of 2019.

can rollover twice as much as their maturing CDs in a week. On average, 6% of outstanding CDs are scheduled to mature in a week. Panel B shows that the average successful CD issue has a higher issue amount and lower offered yield spread compared to a failed CD issue, with a maturity slightly longer than 6 months .

4.2 Key variables

Before moving to the empirical evidence, below we define the key variables used in our analysis:

- **Fail ratio**: for each bank, we compute the daily CD fail ratio as the share of failed CD issues on that trading day over the sum of failed and successful CD issues on the same day, either in terms of issue amount or the number of issues.

- **Spread for successful CD issues (or realized spreads)**: for each CD issue, we compute the spread as the difference between CD offered yield and the same maturity Shibor rate on the same trading date. In some parts of our analysis, we use the weighted average CD spread of all successful issues for bank i on date t, since banks may issue multiple CDs on the same day.

- **Spread for failed CD issues**: we construct spreads for failed issues at the day-bank level following the same procedure as in the case for successful CD issues. Note that the CD yield spread for failed CD issues is not a market equilibrium price.

- **Run on CDs**: the variables defined have so far focused on the CD issue-level. We also define variables that examine the incidence of issuance failures at the bank level, as in fact most theories of credit dry-ups and bank runs deal with creditors of a single institution. We define a *run* dummy at the bank-week level. For each bank i in an event week t,

Table 2: Summary statistics of issuers and CDs

	Mean	SD	p25	p50	p75	N
Panel A: Issuers characteristics						
Asset (RMB bn)	481.48	1131.40	65.63	144.76	317.26	187
ROA (%)	0.96	0.40	0.70	0.94	1.14	184
NPL ratio (%)	1.80	0.77	1.27	1.71	2.12	179
Equity/asset (%)	7.80	1.44	6.82	7.58	8.73	185
Issuer rating	2.37	1.21	1.00	2.00	3.00	187
CD/liability (%)	11.30	6.26	5.83	11.24	15.51	187
# of issue weeks in 2018	28.24	13.05	18.00	29.00	38.00	187
Initial maturity	0.51	0.26	0.27	0.50	0.72	176
Initial issuer rating	2.42	1.21	1.07	2.00	3.00	187
Rollover ratio (%)	216.57	300.97	98.50	144.2	227.85	174
Maturity ratio (%)	5.97	6.51	2.38	3.94	6.94	187
Panel B: Security-level CD characteristics						
CD issues						
Issued amount (RMB mn)	649.03	1492.66	100.00	200.00	550.00	5781
Offered yield spread (bps)	22.79	25.12	7.30	20.00	34.00	5781
CD maturity (year)	0.56	0.36	0.25	0.50	1.00	5781
CD fails						
Issued amount (RMB mn)	312.96	177.27	200.00	300.00	500.00	1233
Offered yield spread (bps)	53.07	28.95	32.90	45.60	76.00	1233
CD maturity (year)	0.59	0.32	0.25	0.50	1.00	1233

Notes: (1) Sample includes all frequent issuers' CD issues and fails in the event window from April 22, 2019 to July 15, 2019. Top panel reports summary statistics of key financial variables from banks' 2018 balance sheets, unless otherwise specified. (2) Issuer rating is coded into three categories, with a higher number corresponding to a lower issuer rating. AAA is coded as 1, AA+ is coded as 2, and AA, AA-, A+ and A are coded as 3. (3) Bottom panel reports summary statistics of issued and failed CDs.

we define $run_{i,t}$ as 1 if the bank's total amount of failed issues as a share of the total attempted issue amount in that week is larger than or equal to 90%:[14]

$$run_{i,t} = \begin{cases} 1, \text{ if } \dfrac{(\text{total amount of failed issues})_{i,t}}{(\text{total amount of attempted issues})_{i,t}} \geq 90\% \\ 0, \text{ otherwise} \end{cases}$$

We use a threshold failure ratio of 90% to define a run because it provides a good solution to the trade-off between the precision of our definition and the number of observable bank runs. This value is high enough that it allows us to focus on banks experiencing the most severe disruption to their ability to access the wholesale market, and filters out potential noisy behaviors due to idiosyncratic shocks and failures. At the same time, a higher cutoff fail ratio would limit the incidence of bank runs that we can observe with our data.

- **Rollover ratio**: we compute the rollover ratio for bank i in week t as the ratio of the total amount of successfully issued CDs to the total amount of maturing CDs in that week.
- **Matured ratio**: the matured ratio for bank i in week t is defined as the total amount of CDs scheduled to mature in the week as a share of the total amount of outstanding CDs at the beginning of the week.

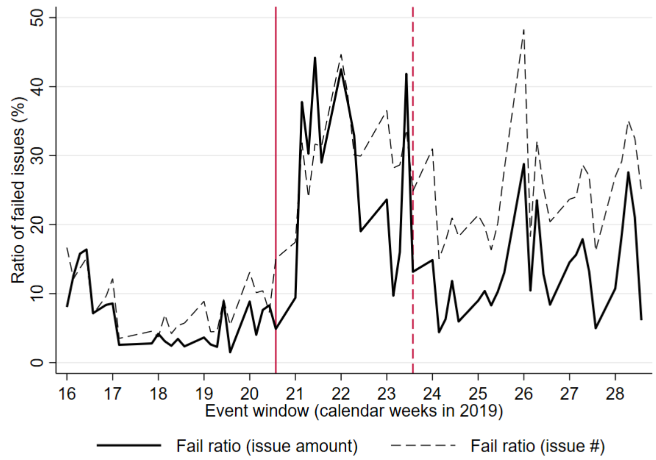
5 Preliminary evidence on CD market fragility

Our data allows us to show that the default event caused significant stress in the wholesale funding market, evidenced by a sharp rise in CD issuance failures, increased spreads and an immediate panic among creditors - a sudden surge in runs (Figure 2). There are visible dynamics in the period right after the default and the period after regulators stepped in. Figure 2a shows that the fail ratio fell after the policy response to the market turmoil. In period 3, we also observe a gap between the fail ratio based on the number of issues and the fail ratio based on issue amounts. This implies that issuance failures are dominated by issues with small amounts in period 3. On the contrary, failed issues are more homogeneous in terms of their size right after the default event.

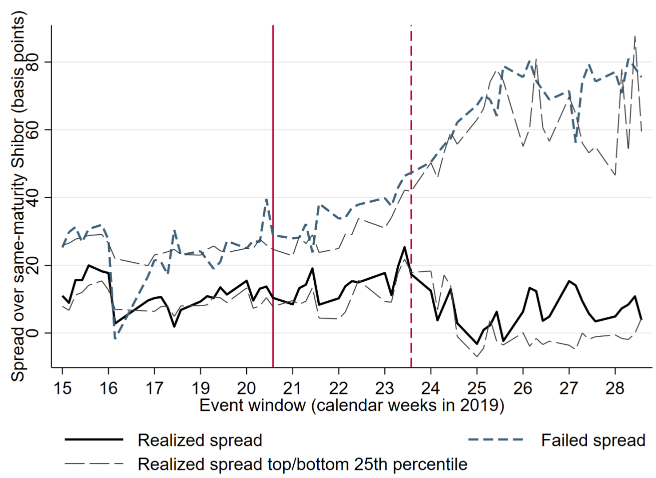
Figure 2b shows that the Baoshang event was followed by an increase in realized spreads (i.e. offered spreads of successfully issued CDs), especially in top 25th percentile. The increase in CD spreads is consistent with the idea that the Baoshang default caused creditors

[14] If a bank does not attempt to issue any CD in the week, then *run* is defined as missing. In other words, the run variable captures the creditors' behavior of not subscribing to a bank's CD, rather than a bank not attempting to borrow.

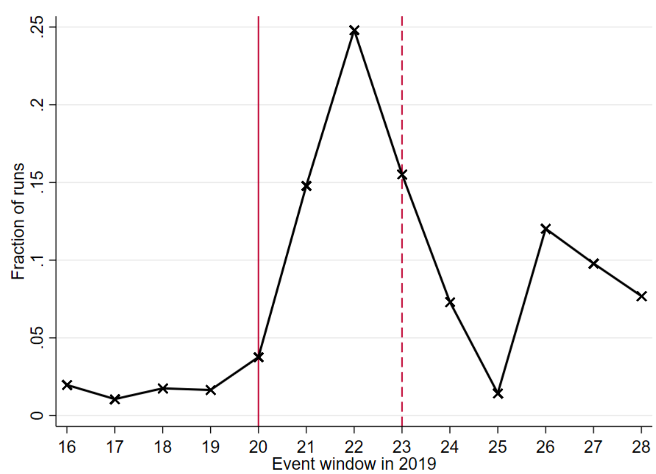
Figure 2: CD market fragility



(a) Daily CD fail ratio



(b) Offered spread: realized vs. failed



(c) Fraction of banks experiencing a run

Note: The first red line marks the date that Baoshang Bank was announced to be taken over by the Chinese authority on Friday, May 24, 2019 (week 20). The second red line marks Friday, June 14, 2019 (week 23) when the Chinese authorities announced explicit backstops for CDs issued by small banks.

to revise their belief in a public guarantee on wholesale funding debt. In this changed market environment, banks had to compensate the creditors for a higher exposure to default risk in order to rollover their CD debts. However, market demand seems to have dried up even for CD issues offering high yield spreads. This is illustrated in Figure 2b, where we show that the average offered spread increased much more for failed CD issues than for successful CD issues in the aftermath of the Baoshang event. This suggests that creditors are unwilling to lend to banks after spreads reach a cap, as in the runs model of Schroth et al. (2014) (which we will discuss in Section 7.2). Clearly, this evidence is only descriptive and it is likely to be affected by selection issues, but we provide a more rigorous test below.

The spike in the fail ratio also corresponds to a surge in runs in the immediate aftermath of the shock, from less than 2% to as high as 25% (Figure 2c). The market-wide panic only became more subdued in period 3. Taken together, our evidence suggests that while banks still experienced CD issuance failures in period 3, market-wide runs consisting of large-scale issuance failures largely ended with the policy intervention. Our run variable is based on failed issuance data, but it also captures the ability of banks to rollover their CDs. In period 2 the average rollover ratio is 260% for banks who did not experience a run, while the average rollover ratio is only 10% for banks that experienced a run. Thus, CD runs lead to rollover risk.

6 Determinants of fails, runs and spreads

The previous section showed that the Baoshang default led to a sudden increase in the probability of CD failures and runs as well as an increase in CD yield spreads. In this section we empirically examine the correlation between these outcome variables and bank characteristics such as ROA, size, book leverage and NPL ratio. The goal is to understand whether issuance failures, runs and spreads have become more sensitive to bank characteristics after the Baoshang default, rather than to establish a causal relation between them. This test is useful to distinguish between different explanations of market stress. For instance, while adverse selection models with private information predict no correlation between spreads and observable bank characteristics, models of fundamental-driven coordination failures (like the one we present in Section 7) predict a significant correlation. We also test whether higher offered yield spreads reduce issuance failures and the incidence of runs. This is a key predictions of standard models of credit markets, according to which market stress is simply due to higher counterparty risk.

6.1 Probability of CD fails

We start by estimating how the probability of a issuance failure correlates with bank and issue-specific characteristics before, during and after the default event. We adopt the following linear probability model:

$$Fail_{i,j,t} = \alpha + \boldsymbol{\beta}\ Bank\ Characteristics_i + \boldsymbol{\theta}\ Controls_j + \varepsilon_{i,j,t}$$

where the dependent variable $Fail_{i,j,t}$ is a dummy equal to 1 if CD issue j by bank i at time t failed and 0 otherwise. The explanatory variables include bank-fixed characteristics and the regression also controls for issue-specific characteristics. We estimate the model separately for each of the three periods in the event window, to understand how the correlation between CD fails and bank fundamentals changes across periods. This approach is similar to Covitz et al. (2013). To better identify the differential effect of bank fundamentals across the three stages of our event window, we also run the following specification:

$$\begin{aligned} Fail_{i,j,t} = \alpha &+ \beta\ Period2_t \times Characteristic_i \\ &+ \gamma\ Period3_t \times Characteristic_i + \boldsymbol{\theta}\ Controls_j + \lambda_i + \delta_t + \varepsilon_{i,j,t} \end{aligned}$$

In this two-way fixed effect model, we focus on one bank characteristic at a time and estimate the coefficients on the interactions with period dummies (the reference period is Period 1). This specification allows us to test whether issuance failures become more sensitive to each bank characteristic after the Baoshang event.

Among the bank-level characteristics we include the following variables: ROA (return on asset) of the issuer, defined as EBIT/total asset, the size of the issuer, defined as the logarithm of total bank asset, NPL ratio, defined as non-performing loans as a share of total outstanding loans, and the book leverage, defined as equity/total asset. These bank financial characteristics are from the end of 2018, the year before the default shock. They are observable by the market participants at the time of the shock. We also include a dummy for low rating, which equals 1 if the credit rating of the issuer at the time of issuance is below AAA.[15] The issue-level controls are the offered yield spread, the issue maturity, and the issue amount scaled by the bank asset.

The results are shown in Table 3. While issuance failures are sensitive to bank fundamentals in the pre-default period 1 (column 1), the sensitivity is lower and the explanatory power of bank fundamentals is weaker compared to period 2. The coefficients of all bank characteristics in period 2 (column 2) are much larger in magnitude and the R-squared is four times

[15] Rating below AAA is considered a relatively lower rating, as most CD issuers are rated as AAA.

larger than in the period 1 regression. These two sets of results imply that issuance failures are weakly related to bank fundamentals and mostly driven by random factors prior to the Baoshang event. However, in the immediate aftermath of the default event, issuance failures are less random and are mostly driven by banks with weaker fundamentals, i.e. lower ROA, lower asset quality, higher book leverage and lower credit rating. Our fixed-effect model confirms the same results using only within-bank variation while controlling for time-varying aggregate shocks. The coefficients on the interaction between the *Period 2* dummy and each bank characteristic are highly significant, with the only exception of the bank's equity ratio. Moreover, the strongest marginal effects are found in period 2 prior to the central bank's intervention in period 3 (column 4-8). Our findings suggest that creditors start to differentiate between borrowers after the Baoshang default has struck down the market belief in a guarantee on wholesale funding debt. As a result, weaker borrowers are exposed to greater rollover risk.

6.2 Equilibrium spread determination

In this section, we study the correlation of CD yield spreads with bank characteristics. We focus on the spreads of successfully issued CDs (or realized spreads) because only these spreads reflect equilibrium market prices. We use similar regressions to those introduced above. The dependent variable is the offered yield spread of a successful issue over the same-maturity Shibor on the issuance date. The independent variables included in the model are identical to those used above.

The results from the CD spread regressions are shown in Table 4. Although it is not easy to identify a pattern by looking at the estimated coefficients from our three period-specific regressions (column 1-3), the overall explanatory power of bank characteristics improves after the default event, as the R-squared is higher in period 2 and period 3 relative to period 1. Moreover, results based on our second set of regressions (column 4-8) show that realized spreads become more sensitive to several bank characteristics after period 1. For instance, spreads are more negatively correlated with size and more positively correlated with a low credit rating after period 1. This suggests that the risk-pricing of CDs becomes more tightly based on bank characteristics after the collapse of the market-perceived guarantee on wholesale funding debt. Interestingly, the *Period 3* interaction terms have larger coefficients than the *Period 2* interaction terms. We interpret this as suggestive evidence that the policy intervention had a positive effect on risk-pricing.

Table 3: Probability of CD fails and bank characteristics

	Dependent variable: CD fail dummy							
	Period 1	Period 2	Period 3	Full event window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ROA	-0.0496**	-0.213***	0.0428					
	(0.0198)	(0.0453)	(0.0261)					
Size	0.00258	0.0331***	0.0210***					
	(0.00456)	(0.0125)	(0.00675)					
NPL ratio	0.0422***	0.110***	0.113***					
	(0.0121)	(0.0234)	(0.0153)					
Equity ratio	-0.0162***	-0.0623***	-0.00778					
	(0.00563)	(0.0110)	(0.00725)					
Low rating	0.0445***	0.247***	0.0333					
	(0.0130)	(0.0260)	(0.0232)					
Period 2 × ROA				-0.261***				
				(0.0884)				
Period 3 × ROA				-0.0738				
				(0.107)				
Period 2 × Size					-0.0790***			
					(0.0116)			
Period 3 × Size					-0.0401***			
					(0.00916)			
Period 2 × NPL ratio						0.126***		
						(0.0385)		
Period 3 × NPL ratio						0.0774**		
						(0.0335)		
Period 2 × Equity ratio							-0.0102	
							(0.0217)	
Period 3 × Equity ratio							0.00761	
							(0.0129)	
Period 2 × Low rating								0.260***
								(0.0317)
Period 3 × Low rating								0.122***
								(0.0335)
Adj. R^2	0.090	0.398	0.310	0.541	0.545	0.553	0.532	0.547
Obs.	2,555	1,346	2,706	6,921	6,955	6,721	6,965	7,011
Issue-level controls	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE				Y	Y	Y	Y	Y
Week FE				Y	Y	Y	Y	Y

This table reports results from regressions on the probability of CD issuance failure at the security-level. The sample spans from April 22, 2019, to July 19, 2019. Period 1 includes 5 weeks leading up to the default (including the default week, week 20). We divide the post-default stage into 2 periods, with period 2 including the first 3 weeks immediately after week 20 but before any material policy response, and period 3 including the 5 weeks after the policy intervention. Columns (1) - (3) use linear probability models for each period separately. Columns (4)-(8) use two-way FE models on the full event window. All regressions control for observable issuer characteristics from the previous year's financial statement, the CD issue amount as a percentage of the issuer's total assets in the previous year and the issuance yield spread. Lower rating is a dummy variable equal to one if the rating of the issuer at the time of issuance is below AAA. Standard errors in parentheses are clustered at the issuer level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Spreads and bank characteristics

	Dependent variable: CD issuance spread							
	Period 1	Period 2	Period 3	Full event window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ROA	1.982**	-0.334	0.526					
	(0.777)	(1.278)	(1.907)					
Size	-3.557***	-6.499***	-9.168***					
	(0.237)	(0.254)	(0.323)					
NPL ratio	2.865***	0.637	8.235***					
	(0.440)	(0.622)	(0.839)					
Equity ratio	-0.869***	-0.811**	-3.694***					
	(0.182)	(0.318)	(0.505)					
Low rating	6.175***	6.987***	35.61***					
	(0.660)	(0.761)	(1.079)					
Period 2 × ROA				-3.505				
				(3.935)				
Period 3 × ROA				-24.10***				
				(7.171)				
Period 2 × Size					-3.922***			
					(0.471)			
Period 3 × Size					-12.53***			
					(0.817)			
Period 2 × NPL ratio						2.206		
						(1.739)		
Period 3 × NPL ratio						13.49***		
						(3.124)		
Period 2 × Equity ratio							0.885	
							(0.744)	
Period 3 × Equity ratio							1.117	
							(1.519)	
Period 2 × Low rating								9.073***
								(1.631)
Period 3 × Low rating								40.57***
								(2.291)
Adj. R^2	0.552	0.681	0.760	0.704	0.778	0.701	0.688	0.810
Obs.	2,350	1,005	2,150	5,695	5,735	5,585	5,748	5,777
Issue-level controls	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE				Y	Y	Y	Y	Y
Week FE				Y	Y	Y	Y	Y

This table reports results from regressions on the yield spread of successful CD issues at the security-level. The sample spans from April 22, 2019, to July 19, 2019. Period 1 includes 5 weeks leading up to the default (including the default week, week 20). We divide the post-default stage into 2 periods, with period 2 including the first 3 weeks immediately after week 20 but before any material policy response, and period 3 including the 5 weeks after the policy intervention. Columns (1) - (3) use linear probability models for each period separately. Columns (4)-(8) use two-way FE models on the full event window. All regressions control for observable issuer characteristics from the previous year's financial statement and the CD issue amount as a percentage of the issuer's total assets in the previous year. Lower rating is a dummy variable equals to one if the rating of the issuer at the time of issuance is below AAA. Standard errors in parentheses are clustered at the issuer level. *** p<0.01, ** p<0.05, * p<0.1.

6.3 Probability of runs on CDs

We next examine how bank characteristics are correlated with the incidence of runs. As defined before, a run occurs whenever the weekly issuance failure rate of a bank exceeds 90%. The econometric specifications and bank characteristics are the same as in previous sections. The only difference is that we replace the issue-level variables with similar measures at the bank or bank-week level. For instance, *initial lower rating* measures how often the issuer receives a rating below AAA in the first four months in 2019 prior to the default shock. As before, all the bank-level characteristics are determined before the sample periods and cannot respond to the incidence of runs. Again we run this regression separately for each period and then on the full event window. Although only sporadic runs occurred before the shock, the pre-default period 1 data can still be useful to analyze the correlation with bank characteristics.[16]

The results are presented in Table 5. Again, the explanatory power of bank fundamentals improves significantly after the default event, with a tenfold increase in the R-squared between period 1 and period 2 (column 1-3). The two-way fixed effect model presented in column 4-8 further confirms that the sensitivity of runs to bank fundamentals increases significantly in period 2 (with the exception of the equity ratio), suggesting that runs are not random, and are driven by weak bank fundamentals. The sensitivity of runs to bank fundamentals is not significantly greater in period 3 than in period 1. This is consistent with the fact that the market is less stressed after the central bank stepped in to provide emergency backstop and credit insurance.

6.4 Yield spreads and market clearing

A possible interpretation of the evidence is that CD issuance failures surged after the Baoshang event simply because offered yields had not yet adjusted to compensate investors for increased exposure to counterparty risk. Under this view, once banks started offering higher yields, the demand for CDs increased, allowing the market to clear. If this hypothesis holds, then we should observe a negative correlation between offered yield spreads and CD issuance failures or runs. We test this conjecture using two alternative regressions. First, we use our security-level data and estimate how the offered yield spread affects the probability of an issuance failure. Second, we estimate how the average offered spread affects the

[16] In our analysis of the correlates of runs, we are limited to use data on banks that have attempted to borrow through at least one CD issue in a given week. Thus, if there are unobservable variables that affect both a bank's decision to issue CDs and the probability of runs, the estimates of regression coefficients may be biased. To address these selection issues, we have also estimated a Heckman two-step model using the bank's reliance on the CD market in the previous year and its rollover need to instrument for the bank's borrowing decision. The selection model gives us similar results to those presented here.

Table 5: Run likelihood and bank characteristics

	Dependent variable: issuer-week run dummy							
	Period 1	Period 2	Period 3	Full event window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ROA	0.0210	-0.0338	-0.00296					
	(0.0257)	(0.0547)	(0.0313)					
Size	-0.00516	-0.112***	0.000508					
	(0.00502)	(0.0185)	(0.00651)					
NPL ratio	0.00791	0.0366	0.0258*					
	(0.00627)	(0.0330)	(0.0143)					
Equity ratio	-0.00432	-0.0106	0.00482					
	(0.00563)	(0.0160)	(0.00740)					
Initial low rating	0.0348**	-0.0192	0.0233					
	(0.0160)	(0.0339)	(0.0224)					
Initial maturity	0.0186	-0.0702	0.0666					
	(0.0247)	(0.0716)	(0.0440)					
Period 2 × ROA				-0.144**				
				(0.0701)				
Period 3 × ROA				-0.0396				
				(0.0589)				
Period 2 × Size					-0.0545***			
					(0.0124)			
Period 3 × Size					0.00692			
					(0.00605)			
Period 2 × NPL ratio						0.0969**		
						(0.0386)		
Period 3 × NPL ratio						0.0312		
						(0.0195)		
Period 3 × Equity ratio							-0.00497	
							(0.0163)	
Period 3 × Equity ratio							0.000670	
							(0.0118)	
Period 2 × Initial low rating								0.154***
								(0.0328)
Period 3 × Initial low rating								-0.0117
								(0.0229)
Adj. R^2	0.048	0.402	0.288	0.540	0.552	0.552	0.515	0.550
Obs.	517	300	498	1,367	1,389	1,336	1,375	1,389
Issue-level controls	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE				Y	Y	Y	Y	Y
Week FE				Y	Y	Y	Y	Y

This table reports results from regressions on the probability of runs at the issuer-week level. The dependent variable is a dummy, assigned value 1 if the bank experiences a run in week t, and 0 otherwise. The sample spans from April 22, 2019, to July 19, 2019. Period 1 includes 5 weeks leading up to the default (including the default week, week 20). We divide the post-default stage into 2 periods, with period 2 including the first 3 weeks immediately after week 20 but before any material policy response, and period 3 including the 5 weeks after the policy intervention. Columns (1) - (3) use linear probability models for each period separately. Columns (4)-(8) use two-way FE models on the full event window. All regressions control for observable issuer characteristics from the previous year's financial statement, weekly CD issue amount as a percentage of the issuer's total assets in the previous year, weekly weighted average CD issue spreads and the average maturity (in years) of all new issues in the first four months in 2019. Initial lower rating represents how often the issuer is rated below AAA in the first 4 months in 2019 prior to the default. Standard errors in parentheses are clustered at the issuer level. *** p<0.01, ** p<0.05, * p<0.1.

likelihood of runs using weekly observations. In this regression, the average offered spread of bank i in week t is constructed as a weighted average of offered spreads across both failed and successful issues by bank i in week t. In both specifications, we use issuer and week fixed effects to avoid selection biases and include further control variables. We run the regressions on the whole event window and estimate interactions of the offered spread with the Period 2 and Period 3 dummies (Period 1 is the reference period).

Table 6: The role of offered-spread in market clearing

	Probability(CD issue fail)	Probability(Run on bank)
	(1)	(2)
Spread	-0.002**	0.119*
	(0.001)	(0.0626)
Period 2 × Spread	0.007***	0.400***
	(0.001)	(0.123)
Period 3 × Spread	0.003***	0.033
	(0.001)	(0.086)
Adj. R^2	0.543	0.545
Obs.	7,011	1,448
Issue-level controls	Y	Y
Issuer FE	Y	Y
Week FE	Y	Y

The sample spans from April 22, 2019, to July 19, 2019. Period 1 includes 5 weeks leading up to the default (including the default week, week 20). We divide the post-default stage into 2 periods, with period 2 including the first 3 weeks immediately after week 20 but before any material policy response, and period 3 including the 5 weeks after the policy intervention. Column (1) reports results from a two-way FE regression on CD fail probability at the security-level, while controlling for issue amount as a percentage of the issuer's total asset in the previous year and issue maturity. Column (2) reports results from a two-way FE regression on the run probability at issuer-week level, while controlling for weekly CD issue amount. In this regression, the spread is the weekly weighted average spread of both issued and failed CDs. Standard errors in parentheses are clustered at the issuer level. *** p<0.01, ** p<0.05, * p<0.1.

The results in Table 6 strongly reject the hypothesis. The coefficients on the interaction between *Period 2* and *Spread*, and *Period 3* and *Spread*, are *not* negative. This means that a higher offered spread does not reduce the probability of issuance failures or the probability of runs in the post-default periods. On the contrary, our results indicate that creditors are less likely to invest in CD issues that offer higher spreads after the Baoshang event. This suggests that the equilibrium spread of CDs may be constrained by a cap above which creditors refuse to lend their funds, thus hampering market clearing in periods of turmoil.

7 A model of wholesale funding runs

To sum up the results from our empirical analysis, the CD runs triggered by the Baoshang event were largely driven by observable bank characteristics and occurred in spite of banks offering higher yields. These findings are consistent with models of fundamentals-driven coordination failures (Goldstein and Pauzner, 2005; Rochet and Vives, 2004; He and Xiong, 2012) that predict banks with weaker fundamentals are more likely to experience runs. In this section, we show that our empirical evidence can be explained quantitatively with models of fundamental-driven coordination failures among creditors. We adapt the model of Schroth et al. (2014), which is based on the dynamic debt runs model of He and Xiong (2012) to the wholesale funding debt of banks, while keeping key model assumptions the same. This is a useful model of CD runs because it features staggered short-term debts that are priced in a competitive market. Our goal is to use a calibrated version of this model to explore the drivers of runs and shed light on important policy implications.

7.1 Model description

We start by briefly describing the model setup and the equilibrium in our environment.

Debt financing: The time unit is one year. At time zero, a bank acquires a long-lived asset, such as a commercial loan. The asset yields a single cash flow which arrives according to a Poisson process with intensity ϕ. We denote by τ_ϕ the random maturity date of the asset. The final cash flow is y_{τ_ϕ}, where y_t follows a geometric Brownian motion with drift μ and volatility σ:

$$dy_t = \mu y_t dt + \sigma y_t dZ_t$$

and $\{Z_t\}$ is a standard Brownian motion.

The bank finances the asset at time 0 by issuing certificates of deposit to a continuum of creditors, for a total amount of 1\$.[17] Certificates of deposit are zero-coupon and we denote by R_t the face value of a 1\$ CD issued at time t. The face value is determined by the market in each instant as described below. Each CD issue matures randomly and independently according to a Poisson process with intensity δ. When $\delta > \phi$ the bank engages in maturity transformation, financing its long-term asset with shorter-term debt. When the CD matures before the asset, the bank needs to roll over the CD at its current face value. Thus, as long as the bank is able to roll over its wholesale funding debt, the total face value of the

[17] Although the model assumes that CDs are the only liability of the bank, this is not an important assumption. Exactly the same model solution obtains if we assume that other liabilities grow at the same rate as the outstanding stock of CDs, i.e. if the ratio of CDs to the bank's total liabilities is constant.

outstanding CD evolves according to:

$$dD_t = \delta D_t(R_t - 1)dt$$

Default risk: The creditors of the bank face default risk at different points over the asset lifetime. At the time of asset maturity, the bank may default if the asset's cash flow turns out to be less than the face value of outstanding debt, $y_{\tau_\phi} < D_{\tau_\phi}$. In this case, even in the absence of coordination failures, the creditors may experience a loss and each creditor obtains only a share of the asset proportional to his face value. Before the asset matures, creditors also face the risk of a premature liquidation when others do not rollover their debt, i.e. coordination failures. Once some creditors choose not to rollover their debt and the bank is not able to raise liquidity through existing credit lines, the bank is forced to liquidate its asset. Forced liquidation generates a cash flow equal to only a fraction α of the asset expected discounted value. If the cash flow generated by forced liquidation is below the face value of outstanding debt, the bank defaults and each creditor obtains a share of the asset liquidation value proportional to his face value. The bank may be able to avoid a forced liquidation if it can obtain liquidity from a credit line or other sources of liquidity. The credit line however fails with probability $\theta\delta dt$ in each instant. Thus, the parameter θ is inversely related to the strength of credit lines.

The default risk faced by the bank's creditors is priced in the CD face value R_t. Creditors are risk-neutral and have discount rate ρ. Then the spread between the face value and the risk-free rate, or simply yield spread (r_t), is determined by requiring that the expected discounted value of investing 1\$ in CDs issued at t is exactly 1\$. Thus, when the likelihood of a default event increases, the yield spread r_t rises to make creditors break even. However, it is assumed that the bank cannot successfully issue CDs with a yield spread above an exogenous cap $\overline{r}$ due to credit rationing or institutional constraints (see Schroth et al. (2014) for a discussion on the rationales for a spread cap).

Rollover threshold: In this model, creditors base their rollover decision on a single state variable, namely the ratio of the asset's fundamental value to the bank's debt, or inverse leverage, $x_t \equiv \frac{y_t}{D_t}$. The inverse leverage evolves according to the following diffusion process:

$$\frac{dx_t}{x_t} = \mu dt + \sigma dZ_t + \delta dt - \delta R_t dt$$

In equilibrium, each maturing creditor chooses to rollover if and only if the current inverse leverage is above an endogenous threshold x^*. Thus, as soon as the inverse leverage reaches x^*, this triggers a run on the bank. Yield spreads also depend on the current inverse leverage of the bank and are generally decreasing in x_t for $x_t > x^*$.

Importantly, the actual value of x^* depends on the fundamentals of the bank through the model parameters, such as μ and σ. Although the model allows for an important role of fundamentals in determining the incidence of runs, runs are exacerbated by coordination failures: creditors may be better off if everyone waited longer to run on the bank (i.e. used a lower x^*), but each of them has private incentives to preempt the others (adopting a higher x^*).

7.2 Empirical implications

Viewed through the lens of our model, the Baoshang event and the subsequent policy response led creditors to adopt different rollover thresholds across distinct periods in the event window. We describe this framework conceptually below:

Period 1 - Prior to the default shock, creditors always roll over with $x^* = 0$: creditors believe that even if the bank asset's cash flow falls short of the outstanding debt, the government will step in to prevent any bankruptcy risk and they will still receive the face value of their CDs. As such, creditors face no default risk and always roll over their debt and CDs are priced close to the risk-free rate, regardless of the bank's inverse leverage ($x^* = 0$). In fact, stylized evidence from period 1 qualitatively fits this prediction: (1) the spread between CD issue yields and the Shibor was narrow and stable, (2) CD issuance failures were sporadic and (3) runs were even rarer.[18]

Period 2 - Immediately after the Baoshang default, creditors rollover only if $x_t > x^*$: markets realize that the wholesale funding debt is in fact exposed to default risk. Instead of choosing to rollover unconditionally as before, creditors begin basing their rollover decision on the threshold rule and pricing CDs accordingly.[19] This leads to a sudden surge in CD runs. Figure 3 illustrates a simulation of a bank whose inverse leverage x_t is below x^* at the time of the Baoshang default (marked by the solid vertical line) and thus experiences a run on impact. Since the threshold x^* depends on bank fundamentals, the likelihood of a bank experiencing a run is correlated with observable bank characteristics. As for banks that still manage to rollover their CDs, they experience an increase in yields, and the yield rise is larger the closer the bank's leverage is to the threshold. The above predictions from the model can explain (1) the sharp increase in failed CD issues in the wake of the Baoshang default and (2) the increased sensitivity of realized spreads to bank characteristics.

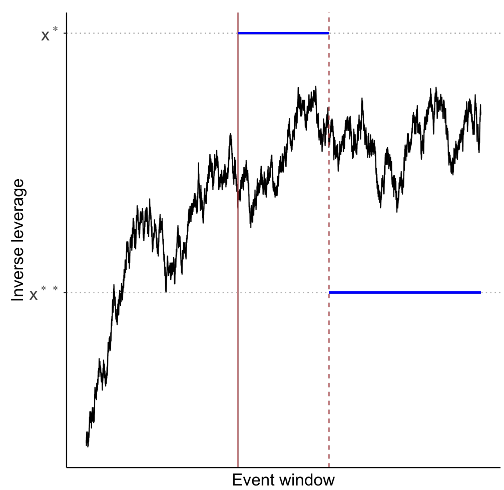
Period 3 - Central bank intervention, creditors rollover at a lower threshold x^{**}: the

[18]For simplicity we assume markets believe in a full guarantee. The same qualitative predictions would obtain if markets believe in a sufficiently large guarantee below 100%. Moreover, to explain the fact that sometimes CD issues fail even before the Baoshang default, albeit at a small rate, it would be possible to add a small exogenous probability that a creditor fails to rollover.

[19]For simplicity, we assume that there is no residual guarantee after the shock.

central bank adopts targeted interventions to address the disruption in the CD market. These interventions can be modeled in a few different ways.[20] First, the intervention may have increased the ability of banks to obtain emergency liquidity, as captured by a decrease in θ. Second, the central bank intervention may have improved the functioning of the CD market, thus leading to an increase in the maximum spread at which creditors are willing to transact, namely the spread cap $\overline{r}$. Numerical analysis shows that both channels result in a decrease in the rollover threshold (see our discussion in Section 7.4), which leads to a lower incidence of runs. Figure 3 illustrates the case of a bank that is able to resume issuing CDs as its current inverse leverage is above the new threshold x^{**} after the policy intervention (marked by the dashed red vertical line). Modeling the policy intervention as an increase in $\overline{r}$ seems particularly promising because it can additionally explain why CD spreads did not fall or even increased for certain banks during period 3 of our event study.

Figure 3: The Baoshang event and rollover thresholds



Note: This figure plots a simulated path of the inverse leverage over the event window. The solid vertical line marks the Baoshang event. The dashed vertical line marks the time of the policy response. The two horizontal lines represent the rollover thresholds: x^* denotes the threshold before the policy intervention and x^{**} denotes the threshold after the policy intervention. In this example, the bank experiences a run in the immediate aftermath of the Baoshang event, but it successfully resumes issuing CDs after the policy response.

7.3 Model calibration

The above discussion suggests that the disruptions in the wholesale funding market caused by the Baoshang default can be qualitatively explained by the model of Schroth et al. (2014). We now calibrate the model and quantitatively assess to what extent important model moments

[20]We assume that the intervention was not anticipated by the market, so that it can be modeled as a unanticipated change in some of the parameters, resulting in a new equilibrium.

can match those obtained from the data. We focus on the model's predictions about three moments: the probability of runs, the mean of yield spreads and the standard deviation of yield spreads. We simulate these moments both in the immediate aftermath of the Baoshang shock (period 2 of our event study) and after the central bank's intervention (period 3 of our event study), for a total of 6 moments. All our simulations are based on a discrete approximation of the dynamics of inverse leverage x_t, starting from a common initial value at the beginning of 2019 denoted x_0. The probability of runs is based on a dummy variable at the week-bank level which equals 1 if the bank's inverse leverage is below the rollover threshold 90% of the time in the week, similar to our definition of the *run* variable in Section 4. Details of the model solution and computation of moments can be found in Appendix A.

We then compute the empirical counterparts to the theoretical moments. Our calibration exercise uses a relatively homogeneous subsample of banks, so that the statistics can be compared to the moments derived from model simulations with a common set of parameter values. The homogeneous subsample consists of banks with initial ROA and size below the sample medians (both criteria are based on the information extracted from the banks' 2018 financial statements). These are banks that were relatively more vulnerable to the effects of the Baoshang event. The empirical counterpart of the run probability is calculated as the average of the *run* dummy variable within each stage. To compute the mean and standard deviation of yield spreads, we weight spreads of successful CD issues by the issuance amount.

Table 7: Model parameters calibration

Parameter	Definition	Value	Calibration
α	recovery rate of a bank's assets	95%	Schroth et al. (2014)
ρ	discount rate	2.55%	average interest rate on 3m CGB in 2019
$\frac{1}{\delta}$	average maturity of CDs	1/0.526	average maturity of CDs in 2019
$\frac{1}{\phi}$	average maturity of bank assets	1/3	macro data and listed-firm data
μ	asset growth rate	0.03	calibrated to match the empirical moments
σ	asset volatility	0.06	same as above
x_0	initial value of bank's inverse leverage	1.03	same as above
θ'	inverse credit line strength before intervention	1.5	same as above
θ''	inverse credit line strength after intervention	0.5	same as above
$\overline{r}'$	yield spread cap before intervention	0.005	same as above
$\overline{r}''$	yield spread cap after intervention	0.02	same as above

Next, we calibrate the model parameters: α ρ, δ, ϕ, μ, σ, x_0, θ and $\overline{r}$. In our calibration we allow the parameters θ and $\overline{r}$ to change after the intervention of the central bank, as discussed above. We thus denote by θ' (θ'') the parameter value before (after) the policy intervention and similarly for $\overline{r}'$ and $\overline{r}''$. Table 7 lists all the parameter calibrations. The parameter α measures the recovery rate of a bank's assets during a forced liquidation. Schroth et al. (2014) estimate α between 92% and 97%. We set α equal to 95%. The discount rate parameter

ρ is set equal to the average interest rate on a three-month Chinese government bond in 2019, equal to 2.55%. The parameter $\frac{1}{\delta}$ measures the average maturity of CDs and thus we set δ equal to 1/0.526, since the average maturity of CDs in 2019 is 0.526 years. Similarly, $\frac{1}{\phi}$ measures the average maturity of bank assets. Since this information is not publicly available from banks' annual reports, we resort to both macro evidence and listed firm-loan data, which give us similar estimates: the average maturity of commercial loans is around 3 years and thus we set ϕ equal to 1/3.[21] Finally, we calibrate the remaining parameters to match the empirical moments. Our exercise yields $\mu = 0.03$, $\sigma = 0.06$, $x_0 = 1.03$, $\theta' = 1.5$, $\theta'' = 0.5$, $\overline{r}' = 0.005$ and $\overline{r}'' = 0.02$.[22]

Table 8: Predicted and empirical moments

	Predicted	Empirical
Before policy intervention		
Run probability	0.50	0.54
Mean of spreads (bps)	25	37
Standard deviation of spreads (bps)	14	11
After policy intervention		
Run probability	0.19	0.20
Mean of spreads (bps)	63	65
Standard deviation of spreads (bps)	54	30

Table 8 reports the empirical moments and the theoretical moments. Our calibration exercise matches the empirical moments closely. The calibrated parameters imply that the rollover threshold is $x^* = 1.03573$ before the policy response and $x^{**} = 1.00005$ after. A lower rollover threshold explains the lower incidence of runs after the policy intervention. The decrease in x^* is in part explained by a lower θ. However, a higher $\overline{r}$ is also needed in order to match the increase in spreads after the policy.

[21] We obtain macro data on the distribution of short-term, medium-term and long-term loans from the PBC while assuming the corresponding maturity to be 1 year, 5 years and 10 years to estimate the average asset maturity. We then cross-check this with evidence from listed firm-bank data from CSMAR, which documents the loan-level information on listed firms' borrowing from commercial banks in China. Loans borrowed from policy banks are not included, as they are mostly development loans with very long terms.

[22] We do not have direct measures for these parameters. Observed leverage cannot be used to estimate x_0 because the model relies on the fundamental value of assets rather than their book value. Indeed our calibration results suggest that leverage is underestimated using book values: the initial value of financial leverage (equity to asset ratio) that best fits the data is around 3%, while mean financial leverage from the 2018 balance sheet data is around 7%.

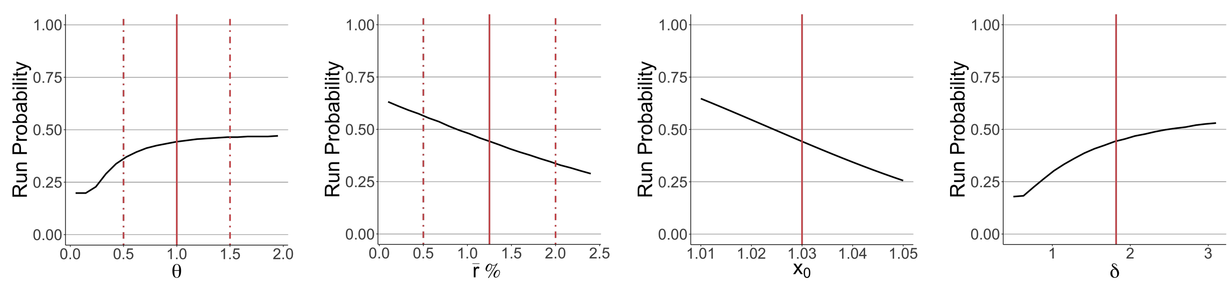
7.4 Policy discussion

In this section, we use our calibrated model to examine the scope and effectiveness of policy interventions aimed at mitigating the incidence of runs, such as liquidity provision and prudential regulation.

Our model suggests policy interventions are warranted because runs affect solvent banks (like in other models of fundamental-driven runs, e.g. Rochet and Vives (2004)). Although the evidence shows that runs are driven by poor bank fundamentals, it is difficult to establish empirically if runs hit mostly insolvent banks or not. However, our calibrated model allows us to back out this information: in the immediate aftermath of the Baoshang event around 63% of runs were hitting solvent banks.[23] This suggests that policies aimed at lowering the rollover threshold can be socially efficient.

We assess four channels through which policy could lower the run incidence using comparative statics based on our calibrated model: (i) emergency liquidity provision, (ii) direct interventions in the CD market, (iii) stringent capital requirements and (iv) regulation of the debt maturity structure.

Figure 4: Sensitivity of run probabilities to selected parameters



(a) Credit lines (b) Spread cap (c) Initial leverage (d) Debt maturity

Note: This figure shows how each of four selected model parameters affects the predicted run probability. To simulate the model we use the same parameter values obtained in our calibration exercise except for θ and $\bar{r}$, which are set equal to the average of their calibrated values before and after the policy response. The solid vertical line in each plot shows the value of the parameter in the baseline calibration of the model. For θ and $\bar{r}$, the dashed vertical lines show the parameter values before and after the policy response.

First, our calibrated model suggests that providing liquidity to banks in distress is very effective in reducing the incidence of runs, as shown in Figure 4a. This could be achieved through the central bank discount window and emergency lending facilities. In our model such policies involve a reduction in θ. Our calibration suggests that θ fell from 1.5 to 0.5 after the central bank's intervention. This change implies that the average number of months a bank can survive in a run before being forced to liquidate assets increased from 4 to 13

[23]We compute this as $1 - \frac{Prob[x_t<1|x_0]}{Prob[x_t<x^*|x_0]}$ where t denotes the time of the Baoshang event.

thanks to the additional liquidity backstops provided by the central bank. Anticipating this, creditors adopted a lower rollover threshold. This channel contributes to a reduction in the probability of runs by around 9 percentage points. A potential cost of these interventions is that they inefficiently delay the liquidation of zombie banks, unless the central bank can condition its liquidity support on bank solvency.

Second, our calibrated model shows that the run probability decreases in the yield spread cap (Figure 4b). The intervention of the PBC is estimated to have lifted the maximum yield spread at which creditors are willing to lend their funds from 50 basis points to 200 basis points, in turn reducing the incidence of runs by 20 percentage points. Our analysis of the empirical evidence showed that during periods of severe stress the CD market functioning is hindered and higher offered spreads do not clear the market. In these circumstances, policy interventions are warranted to "unfreeze" the market. Indeed, the PBC response to the Baoshang event included several measures aimed at supporting the functioning of the CD market, such as accepting the CDs of small banks as collateral and providing additional funding for credit risk mitigation instruments. While we do not have direct evidence on spread caps, our model suggests these measures may have contributed to lowering the incidence of CD runs.

The last two policies we discuss are examples of prudential regulation. Policy-makers could affect the incidence of runs by strengthening the capital requirement on banks, especially on smaller banks that are the most vulnerable to runs because of their thin capital buffers during market-wide funding disruptions. Better capital positions would translate into higher inverse leverage (i.e. lower leverage ratios), which in turn lead to a lower incidence of runs (Figure 4c). The calibrated model predicts the effect is essentially linear and fairly large: a one percentage point increase in the initial equity ratio reduces the run probability by 10 percentage points. One practical limitation of this approach is that the rollover decision of short-term creditors may not be very sensitive to leverage measures based on book values, as highlighted in our empirical analysis. Instead rollover decisions of short-run creditors are likely to be driven by higher frequency measures capturing changes in the fundamental value of the bank's assets, such as real-time news about the firms to which a bank has extended commercial loans.

The last policy channel is based on the liability maturity management of banks. Longer CD maturities (smaller δ values) lead to a lower probability of runs in our model (Figure 4d). Doubling the average CD maturity from 6 months to 1 year (corresponding to a change from $\delta = 1.8$ to $\delta = 1$) is predicted to reduce the run probability by 14 percentage points. Thus, regulators could require banks to issue CDs at a longer maturity to better match the term of their asset holdings. Meanwhile, limiting excessive dependence on interbank business and risk-taking could also reduce smaller banks' reliance on short-term unsecured wholesale funding and improve the maturity structure of their wholesale funding debt.

8 Conclusion

In this paper, we use data on the Chinese wholesale funding market to analyze the effects of a default event that struck the public belief of government guarantees. We document evidence of wholesale funding runs in the wake of the default event. Moreover, wholesale funding spreads and run probabilities became more sensitive to bank characteristics after the default. Fitting the evidence with a model of fundamentals-driven bank runs, we show that coordination failures play an important role in wholesale funding fragility and discuss policies that can reduce the incidence of runs and mitigate the impact of market disruptions.

Our analysis suggests that policies are warranted to reduce the incidence of wholesale funding runs on solvent banks in periods of market stress. However, such policies may also have perverse effects through moral hazard. For instance, knowing that the central bank is committed to provide liquidity backstops in case of emergency, banks may have incentives to adopt more fragile funding structures or to invest in riskier assets. Thus, it may not be optimal for the policymaker to fully eliminate the possibility of fundamentals-driven runs, as they still serve as market discipline mechanisms. This is an important research question that should be further explored both theoretically and empirically.

Appendices

A Model solution and computation of moments.

A.1 Model solution

In order to solve the model we use a similar approach to Schroth et al. (2014). The value of holding on to the bank's CDs for each dollar of face value is given by:

$$\begin{aligned} W(x_t, x^*) = E_t\{e^{-\rho(\tau-t)} \min(1, x_\tau)\, \mathbb{1}_{\{\tau=\tau_\phi\}}\}+ \\ + E_t\{e^{-\rho(\tau-t)} \min\left(1, \frac{\alpha\phi}{\rho+\phi-\mu} x_\tau\right) \mathbb{1}_{\{\tau=\tau_\theta\}}\}+ \\ + E_t\{e^{-\rho(\tau-t)} \max_{\text{rollover or run}} \left[R_\tau W(x_\tau, x^*), 1\right] \mathbb{1}_{\{\tau=\tau_\delta\}}\} \end{aligned} \quad (1)$$

where τ_ϕ is the random time at which the asset matures, τ_θ is the random time at which the credit line fails and τ_δ is the random time at which the CDs held by the creditor mature. Note that the following limit holds:

$$\lim_{x\to\infty} W(x, x^*) = \frac{\phi+\rho}{\phi+\rho+\delta} \quad (2)$$

As discussed in Section 7.1, inverse leverage x_t evolves according to the following diffusion process:

$$\frac{dx_t}{x_t} = \mu dt + \sigma dZ_t + \delta dt - \delta R_t dt \quad (3)$$

Using equations (1) and (3) yields the Hamilton-Jacobi-Bellman equation:

$$\begin{aligned} \rho W(x_t, x^*) = [\mu - \delta(R_t - 1)]x_t W_x(\cdot) + \frac{\sigma^2}{2} x_t^2 W_{xx}(\cdot)+ \\ + \phi[\min(1, x_t) - W(\cdot)] + \theta\delta \mathbb{1}_{\{x_t<x^*\}}[\min(1, \frac{\alpha\phi}{\rho+\phi-\mu} x_t) - W(\cdot)]+ \\ + \delta\left\{\max_{\text{rollover or run}} \left[R_t W(x_t, x^*), 1\right] - W(\cdot)\right\} \end{aligned} \quad (4)$$

Schroth et al. (2014) provide an analytical solution of equation (4) for $x \leq x^*$.

Moreover, it is possible to show that CDs are priced in the following way: $R_t = \frac{1}{W(x_t,x^*)}$ for $x > x^*$ and $R_t = \overline{R}$ for $x_t \leq x^*$, where $\overline{R}$ is the face value cap. Face values R_t and yield spreads r_t are related by the following formula (see Footnote 8 in Schroth et al. (2014)):

$$r_t = (R_t - 1) \times (\phi + \delta) - \rho \tag{5}$$

Thus, the face value cap $\overline{R}$ depends on the spread cap $\overline{r}$ in the following way:

$$\overline{R} = \frac{\overline{r} + \rho}{\phi + \delta} + 1$$

. To solve for the threshold x^* we use the following algorithm:

1. Set a list of values $\tilde{x}$.
2. For each value $\tilde{x}$ in the set, repeat the following:
   (a) Using the expression for (4) in the case $x > x^*$, solve for $W(\cdot)$ numerically for $x \in [0, \tilde{x}]$ using as initial conditions $W(\tilde{x}, x^*) = \frac{\phi+\rho}{\phi+\rho+\delta} - \epsilon_1$ and $W_x(\tilde{x}, x^*) = \epsilon_2$, where the epsilons are small numbers.
   (b) Using the numerical solution, compute x^* as the value x where $W(x, x) = \frac{1}{R}$ (ensuring the value matching condition holds).
   (c) Compute $z_1 = W_x(x^*, x^*)$ using the numerical solution for the case $x > x^*$
   (d) Compute $z_2 = W_x(x^*, x^*)$ using the analytical solution for the case $x \leq x^*$.
   (e) Store the value of $|z_1 - z_2|$ (representing the violation of the smooth pasting condition) and x^*.
3. Choose the value of $\tilde{x}$ with the smallest $|z_1 - z_2|$. If this is below a satisfactory tolerance, then the associated x^* is the solution.

A.2 Computation of moments

In this subsection we describe how we compute the moments from the model. We focus on the model's predictions about three moments: the probability of runs, the mean of yield spreads and the standard deviation of yield spreads. We simulate these moments both in the immediate aftermath of the Baoshang shock (stage 2 of our event study) and after the central bank's intervention (stage 3 of our event study), for a total of six moments. All our simulations are based on a discrete approximation of the dynamics of inverse leverage x_t, starting from a common initial value at the beginning of 2019 denoted x_0. The simulations are based on a set of values for the model parameters: α, ρ, δ, ϕ, μ, σ, x_0, θ, $\overline{r}$. Each parameter takes the same value in stages 2 and 3 of our simulation, except for θ and $\overline{r}$ that have stage-specific values.

Given the parameter values, we first find the equilibrium rollover threshold for each stage using the numerical procedure described above. We also compute the value function $W(x, x^*)$ and the yield spread function, separately for each stage.

Next, we run 10,000 simulations. Each simulation represents a different bank from a homogeneous sample with common parameter values. For each simulation we draw a value of the inverse leverage at the beginning of stage 2, $x_{t'}$, conditional on the initial value x_0. Starting from $x_{t'}$ we simulate a sample path over stage 2 and stage 3, using a discrete-time binomial approximation of the law of motion of inverse leverage, equation (3). In this way, we can track the evolution of inverse leverage and spreads.

For each simulated bank, we compute a dummy variable at the week-bank level which equals 1 if the bank's inverse leverage is below the rollover threshold 90% of the time in the week, similar to our definition of the *run* variable in the empirical part of the paper. Each stage's run probability is computed as the mean of this weekly run dummy variable within the stage across weeks and banks. The mean and standard deviation of yield spreads are computed using average spreads at the bank-week level as observations.

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