Bailing out (Firms') Uninsured Deposits: A Quantitative Analysis*

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Abstract

We document two novel stylized facts about uninsured deposits and bank failures: (i) firms hold more uninsured deposits than households, and (ii) uninsured depositors do not suffer losses in 94% of bank failures, independently of the size of the failed bank. We then construct a quantitative, general equilibrium model designed around these two facts. Reducing bailouts increases bank failures due to runs, but the effects on macroeconomic variables are small unless bank failures affect other sources of firms' liquidity besides deposits. The optimal deposit insurance policy is to provide unlimited coverage for firms' deposits but limited coverage for households' deposits.

Keywords: uninsured deposits, deposit insurance, bailouts, firms' deposits
JEL Classifications: E20, G21, G28, G32

1 Introduction

The failures of Silicon Valley Bank (SVB), Signature Bank, and First Republic Bank in 2023 have turned the spotlight back on the resilience of the financial sector, the effects of bank failures on the economy, and the design of banking regulation. Much has been made of the government's decision to invoke a systemic risk exception to ensure that depositors suffered no losses, even on their uninsured deposits. Importantly, a substantial fraction of the uninsured deposits at these failed banks was held by firms, and a key concern of policymakers was to "minimize any impact on businesses [...] and the economy."[1] Despite the significance of these events, open questions remain

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[1]See https://www.federalreserve.gov/newsevents/pressreleases/monetary20230312a.htm.

about ex-post interventions such as bailouts and ex-ante government guarantees such as deposit insurance—especially for firms' deposits.

In this paper, we make two contributions. We first present novel stylized facts on who holds uninsured deposits, and how often uninsured depositors experience losses when banks fail. We then estimate (i) what would have happened, had depositors in 2023 not been bailed out; and (ii) the optimal level of deposit insurance for firms' and households' deposits. We conduct both counterfactuals using a quantitative general equilibrium model of banking in which both firms and households hold insured and uninsured deposits. Not bailing out uninsured deposits in 2023 would have led to runs on other banks, but the effects on macroeconomic variables are small unless bank failures affect more than just firms' deposits. The optimal policy is to fully insure firms' deposits and only partially insure households' deposits, but the welfare gains are small.

We begin our analysis by documenting our novel facts: (i) firms hold more uninsured deposits than households, both as total stock and as a fraction of their own holdings, and (ii) uninsured depositors rarely face losses when banks fail, even when a systemic risk exception is not invoked. We derive fact (i) by combining the Survey of Consumer Finances with a variety of other public data sources. We find that, as of 2019, 56% of firms' deposits are uninsured, while only 21% of households' deposits are uninsured. Regarding fact (ii), we find that uninsured depositors faced no losses in 71% of bank failures from 1986 to 2008Q4, and in 94% between 2008Q4 and 2020. That is, out of more than 500 bank failures after the collapse of Lehman Brothers in which the FDIC bore losses, uninsured depositors suffered losses only 30 times. The rare losses on uninsured deposits are the byproduct of the way the FDIC resolves failed banks, and not a consequence of "too big to fail": our results are independent of the size of failed banks, and in particular, hold even for small bank failures.

We then construct a structural model designed around the two novel facts. In the model, (i) both firms and households hold insured and uninsured deposits, (ii) uninsured deposits can be bailed out when a bank fails, and (iii) banks fail because of both fundamental shocks and runs. Firms need deposits to pay wages because they face a working capital constraint, and the risk of bank runs is lower when bailouts are more likely. Thus, increasing deposit insurance or bailouts not only reduces runs but also increases output by relaxing the working capital constraint, especially for the most productive firms. However, higher insurance and bailouts strengthen a moral hazard problem in the banking sector, causing banks to be too large and take too much risk.

Using the calibrated model, we find that the macroeconomic effects of not bailing out depositors

in 2023 depend crucially on how bank default affects firm liquidity. If the only liquidity losses for firms are those associated with deposits, the macroeconomic effects are very small. But if bank default affects other sources of firms' liquidity, the effects are much bigger. We model the effects on other sources of liquidity by assuming that bank default results in a tightening of the working capital constraint (Jermann and Quadrini, 2012). We also provide a possible microfoundation of this tightening in an extension in which banks provide liquidity to firms through both deposits and credit lines (Kashyap, Rajan and Stein, 2002), and credit lines cannot be accessed at some failed banks. In this sense, just looking at deposits understates the true losses of liquidity that firms face if banks default.

The small macroeconomic effects that arise when bank failures impact firms only through deposits are due to a confluence of factors that attenuate the impact of bank default. We derive a simple decomposition of the effects of bank failures on firm liquidity provided by deposits to illustrate the robustness of our result. The decomposition relies on sufficient statistics and, thus, can be used to gauge the macroeconomic importance of various policies or economic changes beyond the ones we consider with our model. The factors in the decomposition include the amount of bank failures, the chance depositors will not be bailed out, the fraction of deposits that are uninsured, the losses on uninsured deposits, and the fraction of working capital financed by deposits.

Finally, we use the model to determine the optimal degree of deposit insurance. Under the optimal policy, deposit insurance coverage should be higher than the current $250,000, but it should be different for firms and households. Specifically, the coverage should be unlimited for firms' deposits, but limited at about $525,000 for households' deposits, according to our baseline model. Thus, our results provide a foundation for the *targeted coverage* proposed by the FDIC as one of the ways to reform deposit insurance in the wake of the 2023 bank failures (FDIC, 2023).

From a welfare perspective, however, the gains of moving to the optimal policy are small—as are the effects on real and financial variables. The small effects arise because deposits already have a high degree of protection and rarely experience losses in the current regime. Nonetheless, moving to the optimal policy would shrink the stock of "runnable" liabilities by 88%; the decline in runs would then reduce overall bank failures by 14%. In addition, as in Dávila and Goldstein (2023), the welfare losses of setting deposit insurance coverage too high for households are small, but the losses from removing coverage altogether are large, because reducing deposit insurance greatly exacerbates run risk. Reducing the bailout probability produces even bigger welfare losses, especially when bank default affects other sources of liquidity besides deposits.

Our results are robust to a variety of extensions of the baseline model. In particular, we allow firms to also finance wages using liquid assets other than bank deposits, we design banks so that they can briefly operate with negative equity, and we embed a large amount of moral hazard by allowing banks to engage in socially inefficient risk-shifting (Jensen and Meckling, 1976). In all the extensions, the real effects of reducing bailouts during a banking crisis are small unless bank failures also affect other sources of firm liquidity besides deposits; and in all extensions, the optimal policy is to provide unlimited coverage for firms' deposits and coverage up to a limit for households' deposits. In particular, unlimited coverage for firms remain optimal even in the extension with risk-shifting, even though such an extension embeds a large degree of of moral hazard for banks.

Our novel empirical approach to estimate the insured and uninsured deposits of households and firms can be used for other analyses. We provide an example focusing on households' deposits. We show that households are able to increase the effective insurance on their deposits by about 50% relative to the $250,000 limit, and they do so by exploiting the various FDIC rules that govern deposit insurance. We also show that simplifying the system of *ownership categories* used in determining insurance coverage would not substantially affect the level of insurance coverage, contrary to the concern expressed by the FDIC (FDIC, 2023).

Our work is closely related to four recent papers: Egan, Hortaçsu and Matvos (2017), Dávila and Goldstein (2023), Begenau, Elenev and Landvoigt (2024), and Pancost and Robatto (2023). Egan, Hortaçsu and Matvos (2017) distinguish between insured and uninsured deposits in a structural model of the U.S. banking sector with run-type equilibria, and Dávila and Goldstein (2023) develop a framework that provides guidance for the determination of the degree of deposit insurance using sufficient statistics. Begenau, Elenev and Landvoigt (2024) rationalize the cross-sectional distribution of banks' assets and uninsured deposit holdings, and derive regulatory implications. Relative to these three papers, we distinguish between households' and firms' deposits, which allows us to answer how bailouts affect firms—and through firms, the macroeconomy—and to estimate the optimal level of deposit insurance for firms versus that for households. Pancost and Robatto (2023) also use a model with both households' and firms' deposits, but assume that all deposits are fully insured and focus on capital requirements.

Our analysis builds on a growing literature that uses structural models to study financial regulation (Van den Heuvel, 2008; Davydiuk, 2019; Begenau, 2020; Begenau and Landvoigt, 2022; Corbae and D'Erasmo, 2021; Elenev, Landvoigt and Van Nieuwerburgh, 2021; Dempsey, 2022; Choi, 2022; Meehl, 2022). Relative to this literature, our focus is on deposit insurance and bailouts—differently

from these papers that typically study capital requirements—and our model distinguishes between households' and firms' deposits.[2]

More generally, our paper is related to the broader literature about bank runs, deposit insurance, and bailouts (Diamond and Dybvig, 1983; Gorton and Pennacchi, 1990; Allen and Gale, 1998; Cooper and Ross, 2002; Rochet and Vives, 2004; Goldstein and Pauzner, 2005; Keister, 2016; Allen et al., 2018; Mitkov, 2020). A strand of the literature has focused on the pricing of deposit insurance, and includes Merton (1977), Pennacchi (1987, 2006), Chan, Greenbaum and Thakor (1992), Duffie et al. (2003), Acharya, Santos and Yorulmazer (2009), and Shoukry (2024). Other papers focus on the effects of deposit insurance on the banking system, and include Demirgüç-Kunt and Detragiache (2002), Cucic et al. (2024), Iyer and Puri (2012), and Martin, Puri and Ufier (2018).

Our paper is also part of a growing literature related to the U.S. banking crisis of 2023. Benmelech, Yang and Zator (2023) show that bank branch density (i.e., the ratio of bank branches to deposits) has significantly declined over the past decade, and stock prices of banks with lower branch density declined more after the collape of SVB and First Republic, as such banks experienced larger outflows of uninsured deposits. Chang, Cheng and Hong (2023) provide some stylized facts about the cross-section of banks' in relation to uninsured deposits, and they explain such facts with a novel theory that relates firms' holdings of uninsured deposits with banks' risk-taking behavior. Jiang et al. (2023) show that banks' mark-to-market losses triggered by the increase in interest rates in 2022 are large and expose many banks to the risk of runs by uninsured depositors. Allen et al. (2023*a*) build on Allen et al. (2023*b*) and estimate resolution costs for the FDIC of over $200 billion if the banks identified by Jiang et al. (2023) were to fail, which is well in excess of its fund. Drechsler et al. (2023) show that the uninsured deposit franchise poses a risk management dilemma, as a bank cannot simultaneously hedge its interest rate and liquidity risk exposures. Haddad, Hartman-Glaser and Muir (2023) show that banks' sensitivity to interest rate risk increases as banks become more fragile.

2 Uninsured deposits: institutional details and stylized facts

We begin by providing some institutional details and novel facts about the FDIC insurance of bank deposits and resolution of failed banks. We summarize our discussion in two novel facts. First, firms and other non-household depositors hold more uninsured deposits than households, both as

[2] Meehl (2022) compares capital requirements with imposing a bail-in for holders of banks' unsecured debt, other than depositors.

total stocks and as a share of their own holdings. Second, uninsured deposits rarely realize losses when their banks fail, especially since 2008. This section considers these two facts in turn.

2.1 Fact 1: Non-Households Hold Most Uninsured Deposits

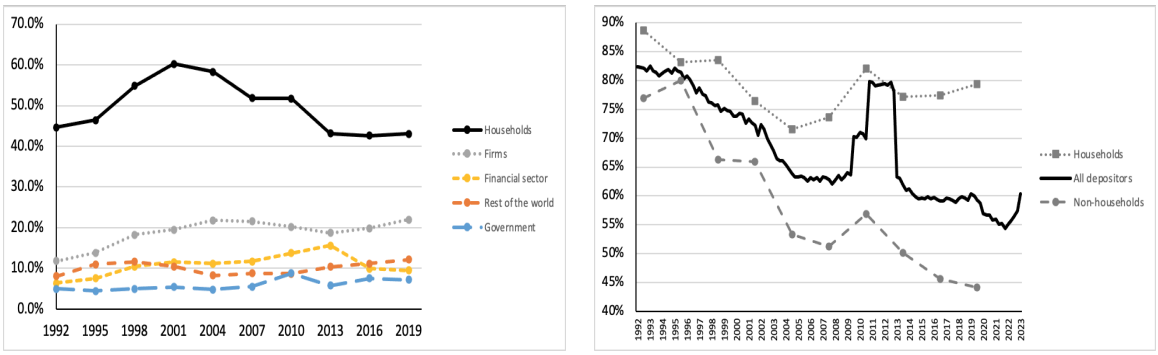
Our first stylized fact is that the majority of uninsured deposits are held by non-household depositors, including firms. To establish this fact, we use data from the Flow of Funds, the FDIC, and the Survey of Consumer Finance (SCF). The design of the SCF in particular allows us to compute the fraction of households' deposits that are insured and uninsured, as we explain below. For the other classes of depositors, we cannot separate firms from other non-household deposit holders (which include financial institutions, foreigners, and governments). Furthermore, because there are no systematic micro-level data that can be used to precisely disentangle firms' deposits into insured and uninsured, we estimate the insurance coverage for firms and other non-household depositors from aggregate data, subtracting out total insured deposits held by households as computed from the SCF.

We compute total uninsured deposits held by households using the SCF. Uninsured deposits, which are typically held by wealthy households, are observable in the SCF because it includes not only a random sample of U.S. households but also a second sample of wealthy households identified on the basis of tax returns, as well as weights to combine the two samples (see e.g. Heathcote, Perri and Violante, 2010). For each household surveyed by the SCF, we use account-level data, including dollars amounts, the identity of the bank, and of the owner(s) of each account. Because the FDIC insurance coverage depends on amount, bank, and owner(s) (see Section 6 below for details), the SCF data allows us to estimate the amount of households' deposits that are insured and those that are uninsured. Additional details about the data construction are provided in Appendix A.1.

The left panel of Figure 1 plots the evolution of the deposits held by households, firms, financial institutions, foreigners, as well as federal, state, and local governments, as a share of deposits at domestic branches of FDIC-insured banks, between 1992 and 2019.[3] Households typically hold between 40% and 60% of the total stock of deposits. The next largest group of depositors are firms (i.e., nonfinancial businesses), followed by financial institutions, foreigners, and government entities.[4] Firms' deposit holdings have nearly doubled from 12% in 1992 to 22% in 2019, in line

[3] We exclude deposits held at foreign branches, which are not insured. We start our sample in 1992 because detailed SCF data that allows us to compute households' insured and uninsured deposits are not available in previous waves of the SCF.

[4] Other account holders (not shown) include nonprofit institutions, with holdings stable at about 4% throughout the entire sample, and domestic hedge funds, for which data are available only since the end of 2012, and whose



(a) Ownership of deposits

(b) Insured deposits, percent

Figure 1. Insured and uninsured deposits

The left panel plots the holdings of deposits of households, firms, financial institutions, foreigners, and governments. For each group, the figure reports the holdings as a fraction of deposits at domestic branches of FDIC-insured banks. The right panel plots the holdings of uninsured deposits for all depositors (solid line), households (dotted line), and non-households (dashed line), as a percent of the total holdings of the respective group.

with the increase in the holdings of cash-like assets documented by Bates, Kahle and Stulz (2009).

Although total deposits are held in roughly equal proportions by household and non-household depositors, we find that the latter hold a significantly higher fraction of uninsured deposits relative to their own holdings. The solid line in Figure 1 plots the fraction of total deposits that are insured, irrespective of the ownership, and is based on FDIC data.[5] The dotted line plots our estimated fraction of households' insured deposits, and the dashed line plots our estimated fraction of non-households' deposits. While all these fractions decreased over time, the fraction of insured deposits is consistently higher for households, in comparison to non-households. As of 2019, the households' share of insured deposits was 79% but only 44% for firms and other non-household depositors.

Figure 2 shows that firms and other non-household depositors hold most of the uninsured deposits. Households held about 30% of all uninsured deposits in 1992. The figure increased to about 50% in 2001, as households' share of total deposits increased, and then decreased after. As of 2019, households held only 22% of the stock of uninsured deposits, despite holding 43% of stock of total deposits.

We can also estimate the stock of uninsured deposits held just by firms—by projecting the insurance coverage shown in Figure 1 to firms' total holding from the Flow of Funds—and compare

holdings have been 1% or less.

[5]The increase in the fraction of insured deposits around the time of 2008 financial crisis is related to the increase of the deposit insurance limit from $100,000 to $250,000 and the government interventions that provided temporary insurance to deposits of any amount on certain transaction accounts until the end of 2012. See Palvia, Shoukry and Stone (2024) for details.

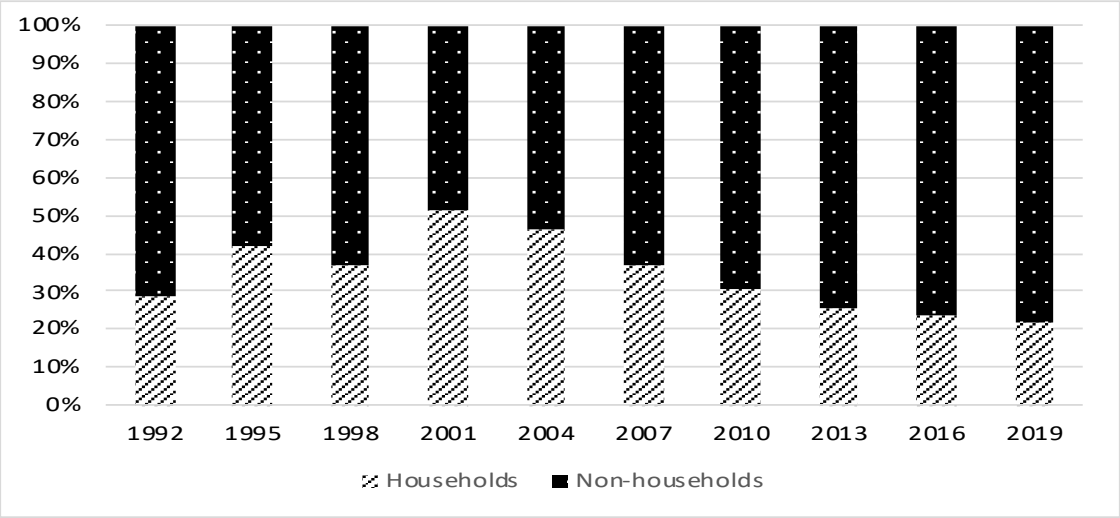


Figure 2. Uninsured deposits by owner

The figure plots the fraction of total uninsured deposits that are held by household and non-household depositors.

them with households' holdings. Focusing on 2019, firms held 58% of the uninsured deposits jointly held by firms and households, despite holding about one third of the total deposits jointly held by firms and households.

Finally, we comment briefly on the accuracy of the estimates in this section. Balloch and Richers (2023) show that the SCF does not provide a full picture of ultrarich households, which could lead us to underestimate aggregate households' uninsured deposits and—because we compute firms' uninsured deposits as a residual—overestimate aggregate firms' uninsured deposits. On the other hand, our approach combines firms and other non-households' deposits, including government deposits; and because local governments can often insure *more* than $250,000, our method might in fact underestimate firms' uninsured deposits.[6] Unfortunately, data limitations do not allow us to quantify which of these two effects dominates. In this regard, the availability of more precise disaggregated data is important to make further progress in the design of optimal deposit insurance, as noted also by Dávila and Goldstein (2023).

2.2 Fact 2: Losses on Uninsured Deposits

Despite the attention paid to the recent wave of depositor bailouts, uninsured depositors rarely realize losses when their banks fail, especially since the 2008 financial crisis. To understand why,

[6]For local governments, time and savings deposits are insured separately from demand deposits in some cases, so that the limit can reach $500,000 per bank, and uninsured deposits might be collateralized by assets held by the banks.

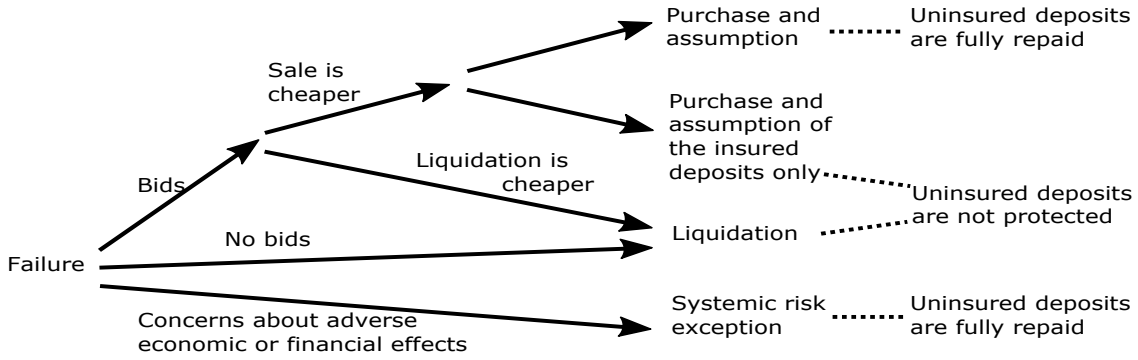


Figure 3. Resolution process of failed banks.

The figure shows how the FDIC resolves failed banks. Liquidation can be implemented in various ways such as deposit payouts (in which the FDIC pays the depositors directly), insured deposit transfer (in which a bank serves as a paying agent for the FDIC), or through the setup of a deposit insurance national bank.

we consider the FDIC's resolution process for failed banks.

When a bank fails, it is taken over by the FDIC, which then begins the resolution process. Typically, the FDIC sells the bank to another financial institution or liquidates it by selling the assets and repaying depositors and other liability holders. If a failed bank is sold, the sale could include all or a fraction of the assets, all the deposits (including the uninsured ones) or only the insured deposits, and a possible agreement in which the FDIC shares losses on certain assets with the acquirer.

The resolution process is represented in Figure 3. The FDIC collects bids from financial institutions that might be interested in acquiring all or part of a failed bank, and then chooses the bid that imposes the least cost to the FDIC. If all the bids entail costs for the FDIC that exceed the cost associated with liquidating the bank, the FDIC is required by law to choose the liquidation option, as it imposes fewer costs for taxpayers. Liquidation is also chosen if no institution submits bids to acquire the failed bank.

The resolution method determines whether uninsured deposits are fully repaid or experience losses. Uninsured deposits experience losses in two cases: if a failed bank is resolved with a sale that includes the transfer of only insured deposits—what is referred to as a purchase and assumption of insured deposits only—or if it is liquidated.[7] If instead the failed bank is resolved with a sale that includes the transfer of the uninsured deposits—simply referred to as a purchase and assumption—

[7] In a sale of a failed bank that includes the transfer of the insured deposits only, the deposits transferred to the acquirer are limited to those that are insured; for the uninsured portion, account holders receive a claim on future dividends financed with the sales of the assets of the bank. We thank the FDIC staff in the Division of Resolutions & Receiverships for a useful conversation about these procedures.

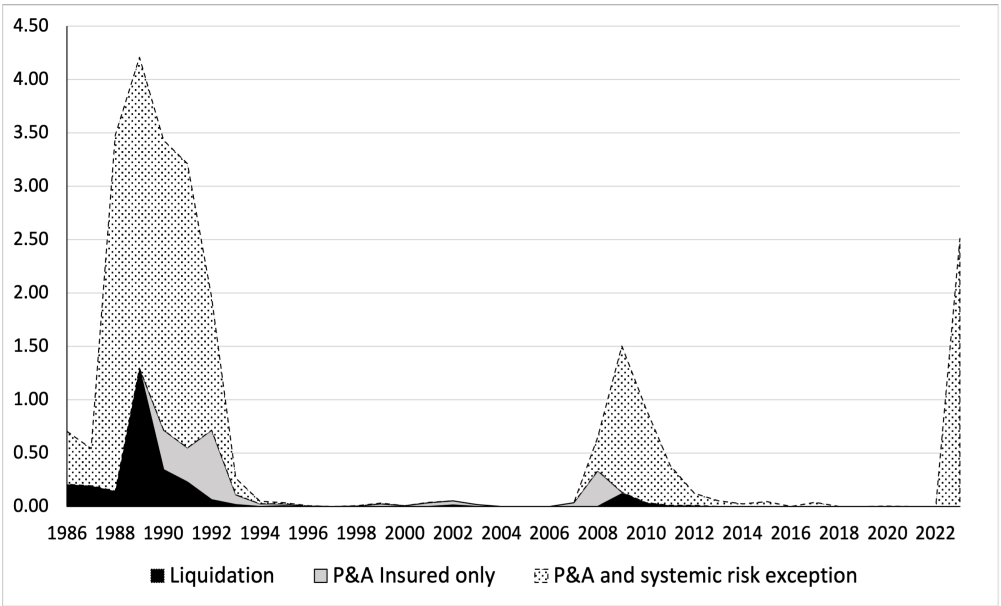


Figure 4. Default rate by resolution

The figure plots the bank default rate (in %) between 1986 and 2023 weighted by deposits, distinguishing between liquidation (black area), purchase and assumption of insured deposits only (gray area), and resolutions in which uninsured deposits do not experience any losses, that is, purchase and assumption and systemic risk exception (dotted area).

the uninsured deposits do not experience losses. Additionally, even if the bank is not sold, the FDIC can fully protect uninsured deposits if the systemic risk exception is invoked, as it was the case for SVB and Signature.

Figure 4 shows that resolution methods that impose losses on uninsured deposits are used infrequently. The figure plots the deposit-weighted bank default rate over time, distinguishing between three types of resolutions: banks that are liquidated (black area), those that are sold but in which only insured deposits have been acquired (in gray), and those that are resolved with no losses on uninsured deposits (dotted area). The overall default rate was very high during the Savings and Loan crisis, the 2008 financial crisis, and the 2023 crisis, and close to zero in the years in between. Liquidation was used to some extent during the Savings and Loan crisis, but its usage declined because of the strain it imposed on the operation capacity of the FDIC, creating considerable deadweight losses (FDIC, 2017). Purchase and assumptions of insured deposits only is also used infrequently.

To formalize the result that uninsured deposits rarely experience losses when banks fail, we consider bank failures between 1986 and 2022 in which the FDIC experiences a loss—thereby excluding cases in which uninsured deposits experienced no losses just because there were enough

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.714***	0.679***	0.686***	0.704***	0.721***	0.775***
	(76.15)	(25.05)	(24.62)	(59.15)	(42.60)	(22.68)
Post	0.228***	0.294***	0.289***	0.244***	0.224***	0.133**
	(16.31)	(5.294)	(5.083)	(10.85)	(10.57)	(2.534)
Log Assets		0.00817				
		(1.384)				
Log Assets × Post		-0.0140				
		(-1.297)				
Log Deposits			0.00649			
			(1.054)			
Log Deposits × Post			-0.0128			
			(-1.145)			
Bank size ($ bn)	All	All	All	< 0.1	0.1-1	> 1
Observations	2,842	2,842	2,842	1,608	1,029	205
R-squared	0.042	0.042	0.042	0.023	0.065	0.022

Table 1. Coverage of Uninsured Deposits

The table reports the results of estimating equation (1) on quarterly bank failure data from the FDIC from 1986Q1 to 2022Q4. The dependent variable is an indicator variable equal to 1 if uninsured depositors face no losses at a failed bank, and 0 otherwise. "Post" is an indicator variable equal to 1 from quarters on or after 2008Q4. "Bank size" denotes the size of the failed bank. Robust t-statistics are in parentheses. *** p <0.01, ** p <0.05, * p <0.1.

junior liabilities (see Appendix A.2 for more details about the sample construction). We then run the following regression:

$$y_{i,t} = \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Size}_{i,t} + \beta_3 \text{Size}_{i,t} \times \text{Post}_t + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is an indicator variable equal to one if uninsured depositors face no loss in bank failure i in quarter t, and zero otherwise; Post_t is an indicator variable equal to one for 2008Q4 and after; and $\text{Size}_{i,t}$ is a measure of bank size at the time of default. We include the Post_t indicator to account for possible changes in the risk of uninsured deposit losses over time, such as those stemming from the reduction in the use of liquidation. In regression (1), the coefficient β_0 represents the average probability that uninsured deposits of failed banks are fully repaid before the 2008 crisis, while $\beta_0 + \beta_1$ represents the average probability afterwards.

The first column in Table 1 shows that uninsured deposits experienced no losses in 71% of bank failures between 1986 and 2008, and in 94% of failures after 2008. Columns (2) and (3) control for

the size of the failed banks, using log assets and log deposits, respectively. Controlling for size does not affect the results, and importantly, the probability of suffering losses on uninsured deposits is unrelated to the size of the banks that fail. To further confirm that the results are not related to size, Columns (4)–(6) repeat the regression in Column (1) by splitting failed banks according to size: less than $100 million in assets, assets between $100 million and $1 billion, and assets above $1 billion.[8] We again find no substantial differences among the subsamples.

Taken together, the results show that uninsured deposits rarely experience losses at failed banks, and that this fact holds true not only for the largest "too big to fail banks" but for banks of any size. This is because the lack of losses arises, most of the time, not from systemic risk exceptions (like in the case of SVB) but from the process of selling failed banks to other financial institutions—which is used for banks of any size.

We have also shown that the frequency at which uninsured deposits experience losses has decreased dramatically after 2008. While this fact is not central to our paper, we provide a brief discussion. Besides the reduction in the use of liquidation, the use of purchase and assumptions with insured deposits only—which imposes losses on uninsured deposits—has been used much less frequently after 2008 as well (see Figure 4). It is an open question whether the infrequent use of this method is due to acquirers' lower willingness to bid for only insured deposits, or changes in the way the FDIC conducts the auction process.[9]

More generally, we note that FDIC could likely reduce its resolution costs by imposing a haircut on uninsured deposits before selling the failed bank. In the current regime, banks must either purchase all of the uninsured deposits at face value, or only the insured deposits; there is no intermediate resolution method in which the uninsured deposits are transferred to the acquiring bank after imposing a haircut, letting the acquirer decide whether to "bail out" the uninsured deposits or not. Thus, the current regime is consistent with the idea that the lack of losses on uninsured deposits arises because of a bailout from the FDIC. We return to this issue in Section 5.2 when discusses welfare and optimal policy in our quantitative model.

[8]The sample of failed banks includes very few large banks, and thus, we can make only limited inference about the losses on uninsured deposits at such banks. For instance, there are only 12 failed banks with assets above $10 billion—or 13 if we include the 1981–1985 period as well. Of these, only two experienced losses on deposits, namely HomeFed Bank and IndyMac.

[9]See also the discussion by Ohlrogge (2023) on this issue.

3 Model

In this section, we describe our quantitative general equilibrium model. Time is discrete and infinite. There are four types of agents in the economy: firms, banks, households, and the government. Firms are subject to idiosyncratic risk, and although each individual firm will grow or shrink depending on the realizations of their idiosyncratic shocks, we construct the firm side of the model carefully in order to maintain aggregation to a representative firm. This keeps the model tractable and allows us to combine (i) rich firms' dynamics with (ii) banks and financial regulation, in (iii) a general equilibrium setting. The last feature is particularly important to recover the effects of shocks and policy changes that operate through prices such as the return on deposits or wages, in line with the arguments in Begenau (2020) and Pancost and Robatto (2023).

Before describing the model in detail in the next sections, we highlight here the main novel elements related to deposit insurance and the possible bailouts of uninsured deposits. We assume that the government insures a fraction ϕ^f of firms' deposits and a fraction ϕ^h of households' deposits. Assuming that deposit insurance applies to a fraction of deposits is necessary to ensure that the model aggregates up to a representative firm and a representative household.[10]

To model the possible bailout of uninsured deposits, and in line with the discussion of Section 2, we proceed as follows. We assume that if a bank fails, the bank is taken over by the government. Uninsured deposits are fully repaid with probability f, and with probability $1-f$, they are subject to an endogenous haircut that depends on the failed banks' recovery rate. The probability f is a simple way to capture the various elements that lead the FDIC to use a resolution method that guarantees the full repayment of uninsured deposits. The case in which uninsured deposits are fully repaid corresponds to resolving a failed bank with a purchase and assumption or a systemic risk exception, and the case in which losses are imposed on uninsured deposits corresponds to liquidation or purchase and assumption of insured deposits.

Bailouts and deposit insurance are distinct policies from the point of view of depositors who are unable to perfectly diversify across banks. Consider a firm with uninsured deposits. The amount of its deposits that are insured is known ex ante, but whether the bank is bailed out or not in the event of failure is uncertain. That is, the gross return on deposits held by a firm is a random

[10] Imposing a dollar limit on deposit insurance would imply that the distributions of wealth across both firms and household become endogenous state variables, leading to significant modeling complications (Krusell and Smith, 1998).

variable $\hat{R}_t^d$ given by[11]

$$\hat{R}_t^d = \begin{cases} R_{t-1}^d & \text{with probability } p_t^{full} \\ R_{t-1}^d \left[\phi^f + \left(1-\phi^f\right)(1-\nu_t)\right] & \text{with probability } 1-p_t^{full}, \end{cases} \tag{2}$$

where R_{t-1}^d is the gross return that was promised to depositors at time $t-1$, p_t^{full} is the probability that uninsured deposits are fully repaid, and ν_t is the haircut on uninsured deposits in the event the firm experiences losses on its deposits. Banks in our model offer a promised return R_{t-1}^d, and this return is paid in two cases which together account for the probability p_t^{full}: (i) the bank does not fail, and (ii) the bank fails and the government bails out the uninsured deposits. Otherwise, the firm experiences losses on its deposits. In this latter case, the fraction ϕ^f of deposits that are insured are fully repaid, but the fraction $1-\phi^f$ that is uninsured is subject to a haircut ν_t that is determined endogenously and depends on the liquidation value of the failed bank's assets.

The risk of receiving only a partial repayment of deposits in equation (2) is idiosyncratic: if depositors were fully diversified across banks, they would only care about the average return on deposits. However, we assume that firms cannot diversify their deposits across banks. Anecdotal evidence (Maruf, 2023) shows that many firms had massive deposit accounts at SVB and other banks that failed in 2023, and the result in Section 2 that 56% of firms' deposits in the U.S. are uninsured indicates that firms might face difficulties in diversifying their deposit holdings. The idiosyncratic risk inherent in equation (2) will affect firms' decisions, and in particular, labor demand.

3.1 Firms

There is a continuum of firms in the economy. The firms are subject to multiple sources of risk: risk that affects their output (both aggregate risk and idiosyncratic risk), and risk arising from the possibility that the firm's bank defaults and its uninsured deposits are not bailed out.

At time t, firm i begins with an amount a_t^i of assets, which are allocated to productive investments (i.e., physical capital) or bank deposits:

$$k_t^i + d_t^i \leq a_t^i. \tag{3}$$

The promised gross return on deposits is R_t^d. However, if the bank where the deposits are held

[11] For households, the expression is the same but with the term ϕ^h to capture the fraction of uninsured households' deposits, which can be different from the fraction ϕ^f for firms.

fails at $t+1$, some deposits might be subject to losses. As discussed in Section 3, we assume that a fraction ϕ^f of deposits are insured, and that a fraction $1-\phi^f$ are uninsured. In case of bank failure, the uninsured deposits are bailed out with probability f. If the uninsured deposits are not bailed out (i.e., with probability $1-f$), they are subject to a haircut ν_{t+1}.

The firm also borrows b_t^i from banks, in the form of a loan with interest rate r_t subject to the borrowing constraint

$$b_t^i \leq \xi_t k_t^i, \tag{4}$$

where $0 < \xi_t < 1$ is subject to an exogenous i.i.d. shock over time.[12] We assume that $\log \xi_t = \log \bar{\xi} + \sigma_\xi \varepsilon_{\xi,t}$, where $\varepsilon_{\xi,t}$ follows a standard normal distribution. Bank loans are used for productive investments, so that the total physical capital used for production by firm i is $k_t^i + b_t^i$.

At $t+1$, after the realization of aggregate productivity A_{t+1} and after learning if the deposits are fully repaid or not, the firm chooses labor l_{t+1}^i with wage w_{t+1} (subject to the working capital constraint described below), and then production takes place. Output is given by

$$y_{t+1}^i = A_{t+1} z_{t+1}^i \left(k_t^i + b_t^i\right)^\gamma \left(l_{t+1}^i\right)^{1-\gamma}$$

where z_{t+1}^i is a productivity shock that is i.i.d. both across firms and over time, taking values z^L and z^H with probability $1-p_z$ and p_z, respectively. The idiosyncratic shock z_{t+1}^i is realized after the firms' decision about physical capital, but before labor is chosen. That is, the amount $r_t b_t^i$ that the firm has to repay to the bank cannot be made contingent on the realization of z_{t+1}^i, but the total wage bill $w_{t+1} l_{t+1}^i$ can be.

Firms require deposits to operate because they face a working capital constraint; in particular, after the aggregate and idiosyncratic shocks are realized, firm i's total labor expenditure is restricted by

$$w_{t+1} l_{t+1}^i \leq \hat{R}_{t+1}^d d_t^i + \bar{\theta} y_{t+1}^i, \tag{5}$$

where $\hat{R}_{t+1}^d d_t^i$ is defined in (2) and $\bar{\theta} \in [0,1]$ parameterizes firms' ability to use their revenues to cover some of their operating expenses, either directly or by pledging future cash flows. In our baseline model, firms can always use their future revenues to access some liquidity, even when their bank fails. In Section 5.1.2, we extend equation (5) so that firms lose access to this source of liquidity if their bank fails and is not bailed out, and show that this additional source of bank-dependent

[12] The shock to the borrowing constraint ξ_t does not affect the key results but allows us to improve the model's fit to several second moments.

liquidity shock—which can be interpreted as the loss of a credit line (Kashyap, Rajan and Stein, 2002) or just as a broader financial shock (Jermann and Quadrini, 2012)—plays an important role in governing the magnitude of the results in the counterfactual analysis.

Inequality (5) is a restriction on l^i_{t+1}: firms have already chosen how much to invest in deposits d^i_t . Having more deposits on hand allows them to hire more labor, which in equilibrium they will want to do when they receive the high shock $z^i_{t+1} = z^H$. Note that the right-hand side of (5) includes the gross return on deposits $\hat{R}^d_{t+1}$, which is less than the promised return R^d_t if the firm's bank fails and the uninsured deposits are not bailed out. That is, losses on the firm's deposit accounts from bank failure will restrict the firm's ability to hire labor and produce output.

After production, the total amount of resources available to the firm is

$$a^i_{t+1} = \underbrace{y^i_{t+1}}_{\text{output}} + \underbrace{(1-\delta)\, z^i_{t+1} k^i_t}_{\text{undepreciated capital}} + \underbrace{\hat{R}^d_{t+1} d^i_t}_{\text{deposits}} - \underbrace{w_{t+1} l^i_{t+1}}_{\text{wage bill}} - \underbrace{r^b_t b^i_t}_{\substack{\text{interest} \\ \text{on loan}}}$$

where $\hat{R}^d_{t+1}$ is the realized return on deposits defined in Equation (2), and capital k^i_t is also hit by the idiosyncratic shock z^i_{t+1}, making it a risky asset.

In order to have a stationary size distribution across firms in equilibrium, we assume that firms exit with exogenous probability p^{exit}. For tractability, we assume that firm exit is independent of both firm i's productivity shock and its size a^i_t. If the firm does not exit, its wealth in the next period is a^i_{t+1}. If the firm exits, it returns a^i_{t+1} to households as a dividend. Households will then control the size of the firm sector by choosing the amount a^{entry}_t invested in new firms (see section 3.3 and Appendix B for details).

Because exiting firms return all their wealth to households, and we assume no agency frictions between firms and households, a firm with assets a^i_t solves the problem

$$V\left(a^i_t\right) = \max_{k^i_t, d^i_t, b^i_t} \mathbb{E}\left\{\beta \frac{\Lambda_{t+1}}{\Lambda_t}\left[\max_{l^i_{t+1}} \left(1-p^{exit}\right) V\left(a^i_{t+1}\right) + p^{exit} a^i_{t+1}\right]\right\}, \tag{6}$$

where the choice of k^i_t, d^i_t, and b^i_t are subject to (3) and (4), and the choice of l^i_{t+1} is subject to (5)—firms choose labor after the realization of all shocks. The term Λ_t in equation (6) is the households' marginal utility (defined in Section 3.3), which firms use to discount future cash flows because households are the owners of the firms. To solve the firms' problem, we conjecture that the borrowing constraint (4) is binding, and that the working capital constraint (5) is binding only for firms hit by the high idiosyncratic shock z^H. We then verify these conjectures ex post in our

simulations.

The optimal choices of the firm are proportional to its wealth, that is, $k_t^i = \phi_t^k a_t^i$ for the choice of capital, $d_t^i = a_t^i \left(1 - \phi_t^k\right)$ for the choice of deposits, and $l_{t+1}^i = \phi_{t+1}^l a_t^i$ for the choice of labor, where ϕ_t^k and ϕ_{t+1}^l are independent of a_t^i and are determined by the first-order conditions discussed below. Note that for a firm with wealth a_t^i, the choice of labor depends on the realization of z_{t+1}^i (i.e., z^H or z^L) and on whether the firms' deposits are fully repaid or not. Because these outcomes are independent, there are four possible states for each firm at $t+1$ (i.e., z^H with fully repaid deposits, z^H with default on uninsured deposits, z^L with fully repaid deposits, and z^L with default on uninsured deposits).

To solve for ϕ_t^k, we denote λ_{t+1}^i to be the Lagrange multiplier of the working capital constraint. The optimal ϕ_t^k solves the first-order condition

$$0 = \mathbb{E}_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \left[\frac{\partial y_{t+1}^i}{\partial \phi_t^k} \left(1 + \bar{\theta} \lambda_{t+1}^i\right) + z_{t+1}^i \left(1 - \delta\right) - r_t \xi_t - \left(1 + \lambda_{t+1}^i\right) \hat{R}_{t+1}^d \right] \right\}. \tag{7}$$

Equation (7) equates the expected marginal benefits of investing in capital to its expected marginal cost. The benefit includes the expected marginal product of capital, as well as the effect of relaxing the working capital constraint (5) since the firm can pledge a fraction $\bar{\theta}$ of its output. The marginal cost includes both the cost of borrowing from banks, $r_t \xi_t$, and the value of the foregone deposit return $\hat{R}_{t+1}^d$. The latter also includes the shadow value of relaxing the working capital constraint (5). Note that the cost of the foregone unit of deposits is uncertain when capital is chosen at time t, because firms do not know whether their deposits will be fully repaid, nor whether inequality (5) will bind.

Because firms choose labor after seeing both their own idiosyncratic productivity shock z_{t+1}^i and their own idiosyncratic deposit return $\hat{R}_{t+1}^d$, the first-order condition for ϕ_{t+1}^l is

$$\frac{\partial y_{t+1}^i}{\partial \phi_{t+1}^l} \left(1 + \bar{\theta} \lambda_{t+1}^i\right) = w_{t+1} \left(1 + \lambda_{t+1}^i\right). \tag{8}$$

For firms hit by the shock z^L, the working capital constraint is not binding and equation (8) reduces to a standard expression equating the marginal productivity of labor to the wage. For firms hit by the shock z^H, equation (8) accounts for the additional costs and benefits of an additional unit of labor choice on the working capital constraint (5): more labor tightens the constraint by increasing the wage bill, but it also loosens the constraint by increasing output on the margin, since firms can

pledge a fraction $\bar{\theta}$ of their output.

3.2 Banks

We assume that a continuum of banks are founded each period t with equity n_t. Banks issue deposits d_t to households and firms and invest their resources $n_t + d_t$ in physical capital b_t, which they loan to firms. Each bank's investment is subject to an idiosyncratic shock ε at $t+1$, which is meant to capture the fact that the bank is unable to perfectly diversify its assets—so that some banks face losses on their own investments. Because banks are subject to limited liability, some banks fail each period. While deposit insurance directly protects some of the deposits at failed banks, the government also acts to protect depositors by bailing out some depositors ex post. Banks can fail either when they receive a bad shock ε, or even when their realized shock is not particularly bad but they face a panic-based run.

3.2.1 Banker's Problem

When a bank is set up at time t, it lends its physical capital b_t to firms. After production takes place at $t+1$, firms return the undepreciated fraction of capital $1-\delta$ plus a return r_t. The resources $b_t(1-\delta+r_t)$ returned by firms are then hit by the idiosyncratic shock ε, which is distributed according to the cumulative distribution function $F_{t+1}(\varepsilon)$, with $E(\varepsilon) = 1$. We assume that $F_t(\varepsilon)$ is lognormal with time-varying scale parameter σ_t; see Section 3.6 for the specification of the law of motion of σ_t. As a result, banks' profits at $t+1$ are given by the cash flow $\varepsilon b_t(1-\delta+r_t)$ net of the repayment $R_t^d d_t$ to depositors, where d_t are total bank's deposits and R_t^d is the gross return on deposits. Thus, banks solve the problem

$$\max_{b_t,\, d_t} \; E_t \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ \varepsilon b_t (1-\delta+r_t) - R_t^d d_t \right\} dF_{t+1}(\varepsilon), \tag{9}$$

where $\mathcal{E}_{t+1}$ denotes the set of ε such that the bank is insolvent—we characterize $\mathcal{E}_{t+1}$ in Section 3.2.3. The bank's maximization problem (9) is subject to the budget and capital requirement constraints:

$$b_t = d_t + n_t \tag{10}$$

$$n_t \geq \zeta b_t \tag{11}$$

where ζ is the capital requirement. Because the return on deposits will always be less than the return on bank's capital, the capital requirement constraint (11) always binds.

Households choose the investment in equity n_t (see Section 3.3). To characterize the return on equity, we note that households can diversify their equity holdings across banks, and failed banks return zero to their equity holders. Thus, the return on bank equity R^n_{t+1} is given by

$$R^n_{t+1} = \frac{1}{n_t} \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ \varepsilon b_t \left(1 - \delta + r_t\right) - R^d_t d_t \right\} dF_{t+1}\left(\varepsilon\right). \tag{12}$$

3.2.2 Bank Runs

To model runs, we assume that uninsured depositors can withdraw their funds at the beginning of $t+1$, after observing the value of ε. In contrast, insured depositors are "sleepy" and always remain in the bank, regardless of the realized value of the shock ε. Such behavior is optimal since insured deposits are always covered by deposit insurance.[13] If uninsured deposits are withdrawn, the bank has to liquidate some of its assets at a fire-sale cost Υ^{tot} to repay the withdrawals. That is, for every dollar of asset liquidated, the bank receives only $1 - \Upsilon^{tot}$, and thus, the bank has to sell $1/(1-\Upsilon^{tot})$ assets to meet each dollar withdrawn.

Banks can fail for two reasons in our model. First, banks hit with a very low realization of ε are fundamentally insolvent: the value of their assets is less than the value of their liabilities, and these banks will fail even without a run. Second, banks that are otherwise solvent may experience a run that can lead them to failure: for intermediate values of ε, the fire-sale cost incurred from selling assets to meet the early withdrawals is enough to drive equity below zero. On the other hand, banks with high realizations of ε remain solvent even if a run occurs. Thus, as in Dávila and Goldstein (2023), a bank's realized shock ε can lay in one of three regions: (i) a fundamental insolvency region, (ii) a run region, and a (iii) a fundamental solvency region. We now characterize these three regions. We denote d^{ins}_t to be the amount of insured deposits, $d^{ins}_t = \phi^f d^f_t + \phi^h d^h_t$, and d^{uns}_t the amount of uninsured deposits, $d^{uns}_t = d_t - d^{ins}_t$.

A bank is fundamentally insolvent if the value of its assets is less than the value of its liabilities, even if it is not subject to a run. The upper threshold $\underline{\varepsilon}^{FUN}_{t+1}$ that defines the fundamental insolvency region is defined by

$$\underline{\varepsilon}^{FUN}_{t+1} b_t (1 - \delta + r_t) = R^d_t d_t. \tag{13}$$

[13] This could be obtained, for instance, by assuming that there is a small cost of trying to withdraw the deposits at the beginning of the period, rather than waiting at the end of the period, so that it is optimal to leave insured deposits in the bank, as they are always fully repaid.

That is, a bank with $\varepsilon = \underline{\varepsilon}_{t+1}^{FUN}$ has just enough assets to pay its depositors, provided there is no run, and a bank with $\varepsilon < \underline{\varepsilon}_{t+1}^{FUN}$ is fundamentally insolvent.

To find the run region, we compute the value of ε such that a bank would have just enough resources to repay insured deposits if *all* the uninsured deposits were to run—requiring the bank to liquidate $1/(1-\Upsilon^{tot})$ of assets per dollar withdrawn. This implies that $\underline{\varepsilon}_{t+1}^{RUN}$ is defined by

$$\underline{\varepsilon}_{t+1}^{RUN}\, b_t\,(1-\delta+r_t) = R_t^d d_t^{ins} + \frac{R_t^d d_t^{uns}}{1-\Upsilon^{tot}}. \tag{14}$$

The left hand side of equation (14) denotes the assets available to the bank, while the right hand side denotes the amount that it must raise to meet is liabilities, given the fire-sale cost. Any bank with $\varepsilon \geq \underline{\varepsilon}_{t+1}^{RUN}$ has enough assets to survive a run, and thus no run occurs for such a bank, whereas banks with $\varepsilon \in [\underline{\varepsilon}_{t+1}^{FUN}, \underline{\varepsilon}_{t+1}^{RUN})$ are in the run region.

Bank runs are coordination failures, and not all banks in the run region actually experience a run. In particular, for each bank in the run region, whether a run occurs depends on (i) the realization of an exogenous sunspot, as in e.g. Diamond and Dybvig (1983) and Dávila and Goldstein (2023), and (ii) the government bailout probability. Item (ii) captures the idea that, if bailouts are more likely, the chances of panic-based runs are lower. Specifically, we assume that the run probability is $\pi\,(1-f)$, where f is the same parameter that governs the ex-post bailout probability.[14] A possible interpretation is that a sunspot occurs with probability π but the government declares, with probability f, that it will support the bank, preventing a run from occurring in the first place. Or, one can view $\pi(1-f)$ as the probability of the sunspot, if the rumors that might trigger a run are less likely to spread in the first place when the bailout probability is higher. We assume that the sunspot is an idiosyncratic shock, so that $\pi(1-f)$ is both the probability that a bank in the run region faces a run and the fraction of banks in the run region that are subject to runs.

3.2.3 Default and Repayment Probabilities

We can now define the set $\mathcal{E}_{t+1}$ of banks that fail and the probability that a depositor's uninsured balance is fully repaid. The set $\mathcal{E}_{t+1}$ of failing banks includes all those that are fundamentally insolvent (i.e., all those with $\varepsilon < \underline{\varepsilon}_{t+1}^{FUN}$) and a fraction $\pi(1-f)$ of those in the run region. The

[14] In general, we could model the run probability as π times a function of the bailout probability f, with the restriction that the run probability is π when $f = 0$ and zero when $f = 1$. To keep the analysis simple, we just assume the function to be linear in f.

fraction $p_{t+1}^{default}$ of banks that fail at time $t+1$ is thus given by

$$p_{t+1}^{default} = \int_0^{\underline{\varepsilon}_{t+1}^{FUN}} dF_{t+1}(\varepsilon) + \pi(1-f) \int_{\underline{\varepsilon}_{t+1}^{FUN}}^{\underline{\varepsilon}_{t+1}^{RUN}} dF_{t+1}(\varepsilon), \tag{15}$$

where the two terms on the right-hand side denote the mass of banks that fail because of fundamental insolvencies and because of runs, respectively. For uninsured depositors, the probability of experiencing no losses (i.e., of being repaid in full) is

$$p_{t+1}^{full} = \left(1 - p_{t+1}^{default}\right) + p_{t+1}^{default} f \tag{16}$$

That is, an uninsured depositor is fully repaid if the bank is solvent (i.e., with probability $1 - p_{t+1}^{default}$), or if the bank fails but the government bails out uninsured deposits (i.e., with probability $p_{t+1}^{default} f$).

3.2.4 Selling Failed Banks

Banks that fail—either because of runs or fundamentals—are immediately closed by the government, who sells the bank's assets to cover the cost of repaying insured depositors and, possibly, bailing out uninsured depositors. The government incurs a proportional loss Υ^{tot} when selling the assets of failed banks, which can be interpreted as a bankruptcy cost. Note that this loss is the same as the fire-sale cost that gives rise to the run region (see Section 3.2.2). Importantly, while Υ^{tot} represents a loss to the government of resolving failed banks, some of that loss may be a windfall for the acquirer of the failed bank's assets. To capture this idea in the model, we follow Elenev, Landvoigt and Van Nieuwerburgh (2021) and assume that a fraction of assets $\Upsilon^{dwl} \leq \Upsilon^{tot}$ is a deadweight loss to society. The remainder $\Upsilon^{tot} - \Upsilon^{dwl} \geq 0$ is a gain to acquirers of assets at failed banks, and the total gains at time t are

$$\Pi_t^{acq} \equiv \left(\Upsilon^{tot} - \Upsilon^{dwl}\right) \int_{\varepsilon \in \mathcal{E}_t} \varepsilon b_{t-1} \left(1 - \delta + r_{t-1}\right) dF_t(\varepsilon), \tag{17}$$

which are distributed lump-sum to households. Setting $\Upsilon^{dwl} \in \left[0, \Upsilon^{tot}\right]$ allows us to flexibly parameterize the difference between private and social deadweight losses; $\Upsilon^{dwl} = 0$ implies that fire sales and bankruptcy costs are a direct transfer from sellers to buyers, with no value lost to society as a whole, while $\Upsilon^{dwl} = \Upsilon^{tot}$ implies that all such costs are deadweight losses.

3.3 Households

Households are infinitely-lived agents who consume, supply labor, and invest in bank equity, bank deposits, and productive firms. Households need deposits to finance some of their consumption expenditure, and hold deposits in a single bank. We design the household problem so that bank failures create only cross-sectional heterogeneity in consumption at the time of the failures, with no impact on wealth. Thus, our model features a representative household, which allows us to easily solve the model in general equilibrium.[15]

Consider a household that starts period t with wealth a_t^h and deposits d_{t-1}^h. There are two types of consumption: c_t^{liq}, which must be financed with deposits (i.e., a deposit-in-advance constraint), and c_t^{oth}, that does not need deposits (i.e., it can be financed with credit or with other assets). The deposit-in-advance constraint for c_t^{liq} is

$$c_t^{liq} \leq \hat{R}_t^d d_{t-1}^h \tag{18}$$

where $\hat{R}_t^d$ is defined in (2). If the bank of the household fails and the deposits are not bailed out, the household will have fewer assets to finance c_t^{liq}.

The budget constraint of the household is

$$c_t^{oth} + n_t + d_t^h + a_t^{entry} \leq a_t^h - T_t + w_t l_t + p^{exit} \int a_t^i di + \Pi_t^{acq} + \left(d_{t-1}^h \hat{R}_t^d - c_t^{liq} \right). \tag{19}$$

The household finances consumption c_t^{oth} and investments in bank net worth n_t, deposits d_t^h, and new firms a_t^{entry} using its wealth a_t^h net of lump-sum taxes T_t, labor income $w_t l_t$, the dividends $p^{exit} \int a_t^i di$ paid by exiting firms, the profits Π_t^{acq} from acquiring failed banks defined in equation (17), and any deposits $d_{t-1}^h \hat{R}_t^d$ not used to finance c_t^{liq}. In equilibrium, the last term will be zero because the deposits-in-advance constraint (18) will always bind.

Households enjoy utility $U\left(c_t^{liq}, c_t^{oth}\right)$, and have disutility from labor l_t that they supply, given by $\chi \frac{l_t^{1+1/\eta}}{1+1/\eta}$. We assume that the utility function $U(\cdot,\cdot)$ is additively separable in the two types of consumption. In particular,

$$U\left(c_t^{liq}, c_t^{oth}\right) = \psi \log c_t^{liq} + (1-\psi) \log c_t^{oth}. \tag{20}$$

[15] Note that relaxing this tractability assumption will likely strengthen our main result that optimal deposit insurance should be lower for households: if households could spread the negative impact of bank failures on both consumption and wealth, the impact of bank failures on households' welfare would likely be smaller.

The additive separability of equation (20) is necessary to ensure that even though households receive idiosyncratic shocks, those shocks imply no cross-sectional dispersion in wealth ex post. We can then construct the value function of households after the consumption of c_t^{liq}. We also guess that the deposit-in-advance constraint is binding, and then we verify that this is the case in our simulations.[16] We now write the household problem, focusing on all the choices but the labor supply—we return to labor supply and the labor market in the next section. The household problem is described by

$$V_t\left(a_t^h\right) = \max_{c_t^{oth}, n_t, d_t^h, a_t^{entry}} (1-\psi)\log\left(c_t^{oth}\right) - \chi\frac{l_t^{1+1/\eta}}{1+1/\eta} + \beta\left\{\psi\,\mathbb{E}_{\hat{R}_{t+1}^d}\log\left(c_{t+1}^{liq}\right) + \mathbb{E}_t V_{t+1}\left(a_{t+1}^h\right)\right\} \tag{21}$$

subject to (19) and the deposit-in-advance constraint (18) evaluated at $t+1$. Wealth in the next period a_{t+1}^h is given by

$$a_{t+1}^h = n_t R_{t+1}^n. \tag{22}$$

Note that as long as the deposit-in-advance constraint is binding, bank failures (which affect only some households in the economy) create heterogeneity in the consumption of c_{t+1}^{liq}, but no heterogeneity in the other household variables, and in particular, in households' wealth. This is because $\hat{R}_{t+1}^d$ only enters in the deposits-in-advance constraint (18). This implies that our model features a representative household, despite idiosyncratic variation in the return on deposits.

The framework gives rise to standard asset-pricing conditions for the supply of banks' net worth n_t and of the wealth a_t^{entry} for new entrant firms:

$$1 = \beta\mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}R_{t+1}^n\right\},$$
$$1 = \beta\mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}R_{t+1}^a\right\},$$

where $\Lambda_t = (1-\psi)(c_t^{oth})^{-1}$ is the marginal utility of consumption of c_t^{oth}, and R_{t+1}^a is the average return of the wealth invested in the firm's sector: $R_{t+1}^a \equiv \int a_{t+1}^i di / \int a_t^i di$.

The first-order condition for deposits is

$$\Lambda_t = \beta\psi\mathbb{E}_t\left\{\frac{1}{c_{t+1}^{liq}}\hat{R}_{t+1}^d\right\}. \tag{23}$$

[16] We also assume that the choice of c_t^{liq} is made before the household observes the time-t aggregate state—the household only knows whether its bank is solvent or fails when it chooses c_t^{liq}. With this assumption, the deposit-in-advance constraint is always binding.

The marginal cost of holding an extra dollar of deposits is the marginal utility of consumption Λ_t. The marginal benefit is the discounted value of increasing the consumption c_{t+1}^{liq} (i.e., the marginal utility $1/c_{t+1}^{liq}$) times the realized return on deposits $\hat{R}_{t+1}^{d}$.

3.4 Labor Market

To produce accurate short-term dynamics in the labor market, we introduce wage rigidities in line with the evidence provided by the macro-labor literature (Shimer, 2005; Gertler and Trigari, 2009; Gertler, Huckfeldt and Trigari, 2020). We assume that households supply labor in a competitive market, but wages are rigid and adjust slowly over time according to the formulation

$$w_t = \omega \, w_{t-1} + (1-\omega) \, w_t^f. \tag{24}$$

The parameter ω indexes the degree to which wages are sluggish and depends on last period's wages w_{t-1}, and w_t^f is the flexible wage that would prevail absent wage rigidities and that is determined by the households' first-order condition

$$w_t^f \Lambda_t = \chi l_t^{1/\eta}, \tag{25}$$

where Λ_t is the households' marginal utility of consumption. The formulation in Equation (24) is similar to the one that Gertler, Huckfeldt and Trigari (2020) derive in a framework in which wage rigidities are microfounded through infrequent renegotiations.

3.5 Government

Following the literature that studies financial regulation in quantitative general equilibrium models, we assume that the government consists of a bank resolution mechanism that is financed by lump-sum taxes. Our novelty is that when a bank fails and is taken over by the government, only a fraction of the deposits are repaid. As discussed in Section 3.2, the government pays off the insured deposits and, in addition, bails out the uninsured deposits that are left in failing banks with probability f.

To calculate the losses for uninsured deposits that are not withdrawn and not bailed out, we note that in practice, the FDIC and uninsured deposits have the same priority, meaning that losses must be shared equally by these two groups of claimants. We define ν_{t+1} to be the haircut imposed

on the uninsured deposits that are not bailed out, and we assume that the haircut is the same for all the banks that fail—as if we were considering an "average" failed bank. Thus, ν_{t+1} is pinned down by the expression that equates the defaulted value of deposits to the value of assets at failed banks:

$$\int_{\varepsilon\in\mathcal{E}_{t+1}} R_t^d d_t \left(1-\nu_{t+1}\right) dF_{t+1}\left(\varepsilon\right) = \int_{\varepsilon\in\mathcal{E}_{t+1}} \varepsilon b_t \left(1-\delta+r_t\right)\left(1-\Upsilon^{tot}\right) dF_{t+1}\left(\varepsilon\right). \tag{26}$$

The left-hand side of equation (26) denotes all the liabilities of the bank. In particular, the haircut is also applied to insured deposits because of the equal seniority among depositors. However, the FDIC (implicitly) reimburses insured deposits for the haircut they experience. The right-hand side of equation (26) denotes the value of the assets at failed banks, net of the default cost Υ^{tot} (see Section 3.2.4).

The government uses lump-sum taxes to finance the costs of deposit insurance and to make insured deposits whole. Its budget constraint is

$$T_{t+1} = p_{t+1}^{default}\, \nu_{t+1} R_t^d \left[d_t^{ins} + f d_t^{uns} \right]. \tag{27}$$

The left-hand side is the total amount collected from households through taxes, and the right-hand side is the total amount paid to depositors at failed banks. In particular, on the right-hand side, $p_{t+1}^{default}$ is the mass of banks that fail, and at each failed bank, the government implicitly reimburses depositors for the haircut applied to the insured deposits and to the fraction f of uninsured deposits that are bailed out.

3.6 Aggregate risk

There are three aggregate shocks in the model: in addition to the shock to the borrowing constraint ξ_t (discussed in Section 3.1), aggregate risk comes from the productivity of firms, A_t, and the variance σ_t of the idiosyncratic bank shock ε. We assume that both the aggregate productivity A_t and the variance σ_t of the idiosyncratic bank shock follow an AR(1) process in logs:

$$\log A_t = (1-\rho)\log \bar{A} + \rho \log A_{t-1} + \sigma_A \varepsilon_{A,t}, \tag{28}$$

$$\log \sigma_t = (1-\rho_\sigma)\log \bar{\sigma} + \rho_\sigma \log \sigma_{t-1} + \sigma_\sigma \varepsilon_{\sigma,t}. \tag{29}$$

We also assume that the shock to the borrowing constraint, ε_{ξ_t}, is correlated with the shock that affects aggregate productivity, $\varepsilon_{A,t}$, with the correlation given by $\rho_{A,\xi}$.

3.7 Aggregate Resource Constraint

The aggregate resource constraint is given by

$$c_t + i_t + \Upsilon^{dwl} \int_{\mathcal{E}_t} \varepsilon b_{t-1} \left(1 - \delta + r_{t-1}\right) \, dF_t\left(\varepsilon\right) \leq Y_t, \tag{30}$$

where total consumption c_t is defined as $c_t = c_t^{liq} + c_t^{oth}$, i_t denotes investments $i_t = (k_t + b_t) - (1-\delta)(k_{t-1} + b_{t-1})$, the term $\Upsilon^{dwl} \int_{\mathcal{E}_t} \varepsilon b_{t-1} \left(1 - \delta + r_{t-1}\right) \, dF_t\left(\varepsilon\right)$ are the deadweight losses from bank default (see Section 3.2.4), and Y_t is gross output defined as $Y_t = \int y_t^i di$. In our quantitative analysis, we follow the standard practice of defining the gross domestic product as the sum of consumption and investments.

4 Calibration and simulation

We now calibrate the model and simulate it using second-order perturbation methods. We then conduct our main counterfactual analyses in Section 5, in which we ask what would have happened had regulators not bailed out uninsured deposits during the banking crisis of 2023 and compute the optimal level of deposit insurance for firms and households.

Table 2 presents the value of the parameters that we use for our quantitative analysis. Because we assume that depositors are able to access the recovery valued of their uninsured deposits at failed banks, and because firms' idiosyncratic shocks are idiosyncratic over time, we choose the length of a time period to be one year.[17] We calibrate the model using data from 1986 to 2019—we begin our sample in 1986 because most regulations that prevented banks from paying interest on their deposits were phased out by 1985 (Gilbert, 1986), and end it in 2019 to avoid the effects of COVID-19.

[17] In practice, depositors do not have immediate access to the uninsured deposits and the FDIC repays them over time as it recovers resources from failed banks, although the FDIC often pays an "advanced dividend" to uninsured depositors based on a conservative estimate of the recovery value. We also note that as SVB failed and before the systemic risk exception was invoked, there were discussions to create a market for the claim on the recovery value of uninsured depositors. The creation of markets for IOUs in case of bankruptcy is a practical possibility—we did observe it when the state of California had a budget crisis in 1992 and paid its employees with IOUs, and major banks honored them as regular checks (Reinhold, 1992). Thus, the choice of one year as the length of period reflects the conjecture that such markets would be created in such a period of time, if major failures without bailouts were to happen.

Panel A: Pre-Set Parameters					
Parameter	Value	Parameter	Value	Parameter	Value
η	1	γ	0.3	$\bar{A}$	1
β	0.95	ρ_A	0.95	$E\{z^i\}$	1
δ	0.1	χ	1	p^{exit}	0.0867
f	0.94	ϕ^f	0.44	ϕ^h	0.79
Υ^{tot}	0.1579	Υ^{dwl}	0.045	ζ	0.0913

Panel B: Parameters chosen to match data moments			
Parameter	Value	Moment Target	Moment Value
z^H	3.98	Pareto tail, all firms	1.062
p_z	4.45%	Pareto tail, incumbents	1.054
ξ	0.242	Firms' deposits/GDP	14%
ψ	0.3375	Households' deposits/GDP	25%
π	0.0966	Bank default rate pre-FDIC	3.8%
$\bar{\sigma}$	0.0372	Average bank default rate	0.64%
σ_σ	0.067	80th percentile bank default rate	0.85%
ρ_σ	0.10	Autocorrelation bank default rate	0.86
θ	0.6525	Deposit premium, $R^f - R^d$	0.91
σ_A	0.0094	Volatility GDP	1.56%
ω	0.725	Vol(employment)/vol(GDP)	0.72
σ_ξ	0.0303	Vol(firms' deposits)/vol(GDP)	4.00
$\rho_{A,\xi}$	0.17	Corr(GDP, deposits)	0.33

Table 2. Calibrated Parameter Values. All second moments are computed by taking logs and applying the HP-filter with parameter 100, both in the model and in the data.

The top panel of Table 2 includes the parameters that we pre-set based on values commonly employed in the literature or external evidence. These parameters include the discount factor β, the Frisch elasticity of labor supply η, the depreciation of capital δ, the exponent of capital γ in the production function, and the autocorrelation ρ_A of the aggregate productivity shocks. We normalize the disutility of labor χ, the average aggregate productivity $\overline{A}$, and the mean of the idiosyncratic productivity shock $E\left\{z^i\right\}$ to one. We set the exit probability p^{exit} to 8.67% to match the average firm exit rate from 1986–2019 in the Business Dynamic Statistics (BDS) of the US Census Bureau.

The remaining parameters in the top panel of Table 2 govern the banks' building block of the model and the government guarantees of deposits. We use the evidence discussed in Section 2 to

set the bailout probability f to 94%, the share of insured firms' deposits ϕ^f to 44%, and the share of insured households' deposits ϕ^h to 79%. To set the liquidation costs and the deadweight losses of bank default, we follow the approach of Elenev, Landvoigt and Van Nieuwerburgh (2021) and use the evidence in Bennett and Unal (2015) to set the liquidation cost parameter Υ^{tot} to 15.79% and the deadweight loss parameter Υ^{tot} to 4.5%, based on data about the total resolution costs and the total receivership expenses of failed banks, respectively, weighted by assets. The capital requirement is set at the average level of equity capital to assets in our sample, that is, 9.19%. This is also nearly identical to the level at the end of 2022.

The bottom panel of Table 2 lists the values of the parameters that are chosen to match selected data moments. We calibrate the parameters which govern the idiosyncratic shocks that firms face, z^H and p_z, to match the extreme skewness of the firm size distribution (Luttmer, 2007), and set z^L based on the normalization $\mathbb{E}\left\{z_t^i\right\} = 1$. In particular, the model matches the fact that the right tail of the firm size distribution is Pareto, and we set z^H and p_z to match the Pareto tail coefficients in the data. We distinguish between the distribution of all firms—which has a Pareto tail coefficient of 1.062—and that of incumbent firms (i.e., those that are one year or older) whose Pareto tail coefficient is 1.054. Additional details are provided in Appendix B.

The parameters ξ and ψ govern the average stock of firms' and households' deposits as a fraction of GDP. In the data, these fractions are measured as described in Section 2.1.[18]

To calibrate the sunspot probability π, we follow Dávila and Goldstein (2023) and set π so that the model matches the pre-FDIC bank default rate when shutting down government interventions—in our model, bailouts and deposit insurance. We target a 3.8% default rate, which is the deposit-weighted failure rate for the period 1921-1933.[19] When running the model with no government interventions, we make two modifications to better align it with the conditions in the banking system in 1921-1933 period. First, we set ζ to 13% to match the capital-asset ratio for that period. Second, we extend the model to account for the double liability, that is, the fact that bank shareholders would not only lose the amount invested but were also liable for an additional amount equal to their investment, in the event of default. Additional details are provided in Appendix C.

To calibrate the remaining parameters, we use targets that are commonly employed in the quantitative banking literature such as bank default rates, the liquidity premium on deposits, and

[18]Firms' deposits as a fraction of GDP display a trend throughout the entire sample, and thus, we use the last observation of the sample as the target. For households' deposits, there is trend that ends around 2001, so we start the sample in 2001 to compute this target.

[19]Our calculations are based on the data available at https://www.fdic.gov/bank/historical/managing/chronological/pre-fdic.html.

volatilities of macroeconomic and financial variables. Additional details are in Appendix D.

Appendix E provides a list of untargeted moments and compares the behavior of the model with the data. The model matches reasonably well several untargeted business cycle and banking moments.

5 Counterfactual analysis: The 2023 banking crisis, bailouts, and optimal deposit insurance

We use our calibrated model to run two counterfactual analyses. First, we ask what would have happened had regulators not bailed out uninsured deposits during the banking crisis of 2023. Second, we ask what the optimal level of deposit insurance is, allowing for different level of coverage for firms and households.

5.1 The 2023 banking crisis and the reduction in bailouts

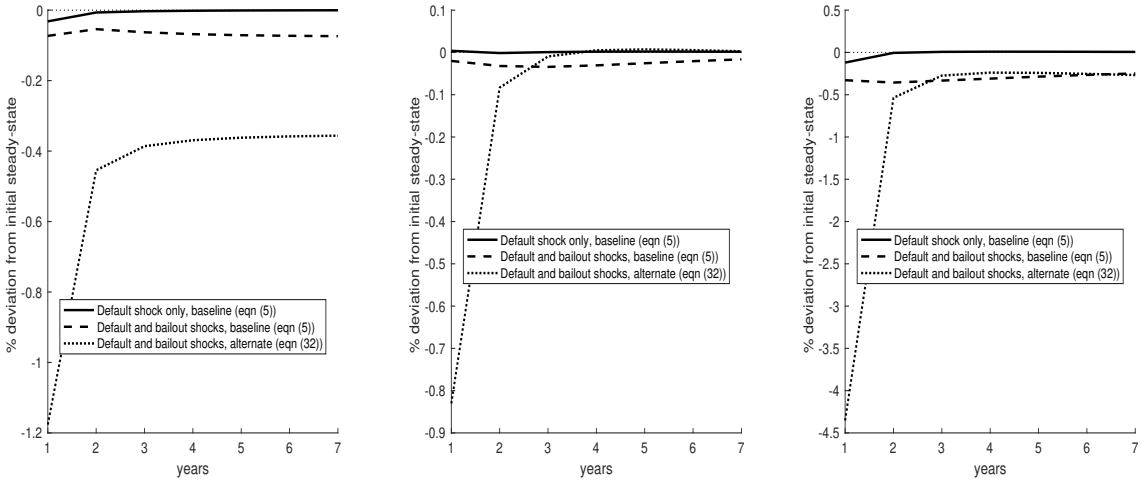
To study what would have happened had regulators not bailed out uninsured deposits during the banking crisis of 2023, we use the calibrated model to compute the impulse responses to two shocks: a *default shock* that temporarily increases the default rate of banks, to produce the 2023 banking crisis, and a *reduced bailout shock* that permanently lowers the probability f that the government bails out the uninsured deposits of failed banks.

We find that the macroeconomic effects of reducing bailouts during a banking crisis are small when—as in our baseline model—the only liquidity losses for firms are those associated with uninsured deposits. In section 5.1.2, we provide a simple extension and show that, if bank failures simultaneously reduce firms' deposits and their access to other forms of liquidity, reducing depositor bailouts has a much larger effect on the macroeconomy.

5.1.1 Lower bailouts: main results

We model the 2023 banking crisis by setting the shock σ_t that affects banks' default so that—absent any changes to the bailout probability f—2.3% of the banks in the economy are insolvent. We choose this value to match the failures that took place in the first and second quarter of 2023, which account for 2.3% of the assets of FDIC-insured banks.

We then add a second shock—to the bailout probability f. We reduce f from its baseline value of 94% down to 35%. To arrive at a new value for f of 35%, we note that had there been no



(a) GDP (b) Employment (c) Investments

Figure 5. Response to the default and reduced bailout shocks

The figure plots the dynamics of GDP (left panel), employment (middle panel), and investments (right panel) in percent deviations from the initial steady state. The solid lines in each figure plot the dynamics for the baseline case where there is only a shock that increases the probability of bank default, and the working capital constraint is given by inequality (5); the dashed lines plot dynamics with both the bank default shock and the shock that permanently reduces the probability f that uninsured deposits are bailed out. The dotted lines plot dynamics for both shocks, but for the case where the working capital constraint is given by inequality (32).

bailouts at all in 2023, the asset-weighted ratio of banks receiving a bailout from September 2008 to the first quarter of 2023 would have been approximately 35%.

The announcement of a permanent reduction in the bailout probability f leads to a substantial increase in bank failures. When adding the reduced bailout shock, the default rate increases from 2.3% to 3.5%. This result arises because the probability of bank runs in the model is a function of the bailout probability f, as discussed in Section 3.2.2. In other words, the model implies that not bailing out banks in the midst of a banking crisis leads to a sizeable banking panic, something regulators were surely keen to avoid in the spring of 2023.

Although reducing the bailout probability f leads to a substantial increase in bank failures, the consequences for the real economy are small. The solid and dashed lines in Figure 5 report the impulse responses both when f is constant at 94%, and when f is unexpectedly reduced to 35%, respectively. While adding the bailout shock slightly worsens macroeconomic outcomes, there are virtually no real effects in both cases.

The model produces small macroeconomic effects of reducing f because the only consequence of

bank failures for firms is through their deposit holdings. Losses on firm deposit holdings have real effects because they limit how much labor firms can hire, due to the working capital constraint (5). However, the way bank failures propagate to labor demand through firms' deposits is mediated by several factors. Equation (31) lists each one, along with an estimate of its importance:

$$\underbrace{3.5\%}_{\substack{\text{bank}\\\text{failures}}} \times \underbrace{65\%}_{\substack{\text{depositors}\\\text{not bailed out}}} \times \underbrace{56\%}_{\substack{\text{uninsured}\\\text{deposits}}} \times \underbrace{16\%}_{\substack{\text{losses on}\\\text{uninsured deposits}}} \times \underbrace{15\%}_{\substack{\text{wages financed}\\\text{by deposits}}} = 0.03\%. \tag{31}$$

First, our model suggests that 3.5% of banks would have failed, and because we set the bailout probability to $f = 35\%$, deposits would have not been bailed out at $1 - f = 65\%$ of banks. Next, recall that 56% of deposits are uninsured according to the evidence presented in Section 2.1. In addition, at failed banks, uninsured deposit losses are on average 16%. Finally, our model suggests that the stock of firms' deposits represents 15% of wage payments.

Overall, equation (31) implies that the drop in labor demand as a result of the shocks to σ_t and f is 0.03%. This back-of-the-envelope calculation is very close to the 0.02% reduction in employment predicted by the model—the general equilibrium response of wages contributes to the difference.

Equation (31) is also a useful tool for estimating the robustness of our results in the spirit of the sufficient statistic approach. We next provide a few illustrative examples.

Suppose that firms' deposits are disproportionately concentrated in run-prone banks—as was the case for SVB. Assuming that the banks that fail have only firms' deposits, the estimate in (31) increases by a factor of three—this is because the average bank in our model has one-third of its deposits held by firms—resulting in a reduction in labor demand of about 0.09%. Likewise, assuming that firms finance 100% of their working capital with bank deposits—which is likely an overestimate—results in only a 0.2% drop in labor demand.

Alternatively, if one wants to consider the case in which firms lose all access to their uninsured deposits at defaulted banks in the short run—because it takes time for the FDIC to reimburse such deposits—then the 16% loss-on-deposits figure should be replaced with 100%. The resulting loss of liquidity is still only 0.19%. This is again an upper bound, as the FDIC often pays an advance dividend to provide a partial reimbursement to uninsured depositors soon after a bank fails, or in the case of SVB, the banking industry was discussing—before the systemic exception was invoked—how to create a market to allow depositors to sell their claim to uninsured deposits to quickly recover the liquidity they needed.

While some factors could increase our estimate, there are others that might reduce it. For instance, in our model, the government intervenes immediately to take over a bank subject to a run, but in practice, some depositors are able to withdraw their deposits. If 25% percent of depositors are successful at withdrawing—in line with the evidence of Martin, Puri and Ufier (2018) and the withdrawals during the run at SVB (Federal Reserve Board of Governors 2023)—any estimate based on Equation (31) are reduced by one-fourth. In this regard, note also that the role of social media in increasing the speed of a run—which is sometimes mentioned as a risk for financial stability (Cookson et al., 2023; FDIC, 2023)—can actually result in more deposits being withdrawn before a failing bank is shut down, reducing the impact on the macroeconomy.

Ultimately, the small real effects that we estimate through the lens of our quantitative model are driven by a confluence of factors that insulate aggregate employment from the bank failure shock. Equation (31) represents our best estimate of each factor, and while each estimate is uncertain, taken all together they suggest that the implications of our model are likely robust.

5.1.2 Generating Larger Macroeconomic Effects

The lack of large macroeconomic effects we find in section 5.1.1 arises because, in the model, the only effects for firms that face the default of their own bank are related to the liquidity lost through uninsured deposits. In this section we extend the model to allow bank failures to affect not only firms' deposits, but their other sources of liquidity as well.

We find that an unexpected reduction in bailouts during a banking crisis has large real effects when bank failures affect not only firms' deposits, but also their other sources of liquidity. To model how firm liquidity responds to bank failure, we assume that firms are unable to pledge future cash-flows to finance their working capital when their bank fails. In other words, we replace equation (5) with

$$w_{t+1} l^i_{t+1} \leq \begin{cases} R^d_{t+1} d^i_t + \bar{\theta} y^i_{t+1} & \text{with probability } p^{full}_t \\ R^d_{t+1} d^i_t \left[\phi + (1-\phi)(1-\nu_t)\right] & \text{with probability } 1 - p^{full}_t \end{cases}, \tag{32}$$

so that firms whose bank defaults are hit with two simultaneous shocks: not only do they lose a fraction of their uninsured deposits, but they are also unable to unable to pledge future output. In Appendix F, we provide one possible microfoundation for equation (32) by assuming that firms pledge output to borrow from banks through credit lines. When a bank fails and is not bailed out,

firms both face losses on uninsured deposits and cannot access their credit lines.[20]

The real effects of reducing depositor bailouts are much larger in this version of the model. The dotted lines in Figure 5 plot the response of GDP, employment, and investment when the economy is hit by both the default and reduced bailout shocks, and firms face the working capital constraint (32). GDP drops by 1.2%, employment by 0.8%, and investments by 4.5%; in other words, the reduction in f leads to a moderately severe recession.

The main takeaway of these results is that if the *only* effect of bank failures on firms' liquidity are those related to uninsured deposits, the implications for macroeconomic variables are small. Thus, just looking at deposits might understate the true losses of liquidity that firms face if banks default and halt their operations.

5.2 Optimal Deposit Insurance

In this section, we determine the optimal deposit insurance policy, assuming that the regulator can apply different levels of coverage to firms' and households' deposits. We find that the optimal policy consists of *targeted coverage* that distinguishes between the protection given to firms' and household' deposits.[21] Specifically, welfare is maximized when firms' deposits are fully protected but households' deposits are only partially protected. Such a targeted coverage policy is optimal regardless of how we specify firms' working capital constraint. That is, we get the same result whether the working capital is given by (5)—which produces small real effects of changing the bailout policy (see Section 5.1.1)—or given by (32)—which produces large real effects (see Section 5.1.2).

In the model, higher deposit insurance improves welfare through three channels: it increases total output by relaxing firms' working capital constraint, it increases household utility by relaxing their deposits-in-advance constraint, and it reduces the size of the run region, thereby lowering the fraction of banks subject to a run. On the other hand, deposit insurance is subsidized and, thus,

[20]This is consistent with the way bank failures are resolved in practice. When uninsured depositors are protected through systemic risk exceptions or the sale of the failed bank to another financial institution, the operations of a bank including the provision of credit typically continue normally. If instead the failed bank is liquidated—which is the main case in which uninsured depositors experience losses—the role of the FDIC as received "generally precludes continuing the lending operations of a failed bank." See the sections "Lines of Credit" in https://www.fdic.gov/resources/resolutions/bank-failures/failed-bank-list/borrowers/.

[21]The FDIC has suggested targeted coverage—with full coverage for business payment accounts—as possibly the best option, in their view, to reform deposit insurance in the wake of the 2023 bank failures (FDIC, 2023, Section 6). In the past, the FDIC has implemented one form of targeted coverage with the Transaction Account Guarantee (TAG) program, from October 2008 through 2010. The program provided unlimited coverage for certain types of transaction accounts. For more on the TAG program see Palvia, Shoukry and Stone (2024).

leads banks to be too big, implying a welfare cost of deposit insurance.

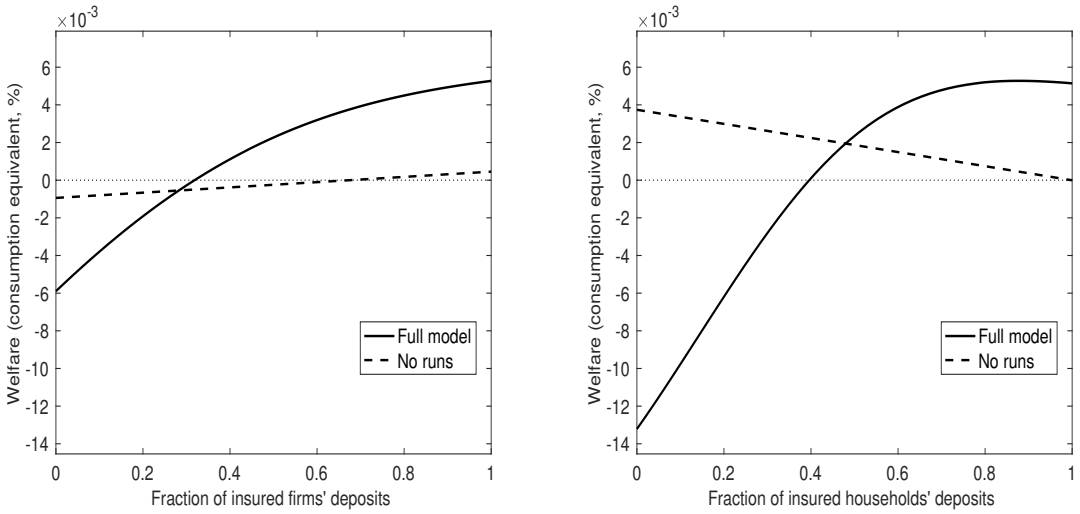
We compute the optimal policy by maximizing the welfare function (i.e., households' utility) with respect to the level of deposits insurance for firms' deposits (i.e., ϕ^f) and for households' deposits (i.e., ϕ^h). That is, we compute the pair $\left(\phi^f, \phi^h\right)$ that maximizes welfare. We calculate welfare as the economy converges to the new stochastic steady state, and we average across different economies with different paths of aggregate shocks and different initial conditions of the state variables randomly drawn from the ergodic distribution of the baseline model. In all simulations, we maintain the bailout probability unchanged at $f = 94\%$.

Figure 6 shows that the optimal level of deposit insurance is 100% for firms and 88% for households, in our baseline model where the working capital constraint is given by (5). In both panels of Figure 6, the solid line reports the benchmark model results, and the dotted line reports the welfare for a model in which there are no bank runs ($\pi = 0$). In the extension in which bailouts also lead to other losses of liquidity (i.e., when the working capital constraint is given by (32)), the results are similar: it is optimal to insure a slightly higher share of households' deposits, namely, 95%, but full coverage of firms' deposits remains optimal.

The 88% optimum for households is somewhat higher than the current value of 79%; we use the SCF to estimate that implementing 88% deposit insurance for households would require a deposit insurance limit of about $525,000, i.e. more than doubling the current coverage limit.[22] However, the welfare gains from changing to the optimal level of insurance are small—about half a basis point, in terms of consumption equivalent. To put this value in context, Begenau (2020), Begenau and Landvoigt (2022), and Pancost and Robatto (2023) find that setting capital requirements optimally would increase welfare by just over 3, 5, and 20 bps of annual consumption, respectively. The small welfare effects of moving to the optimal level of insurance arise because uninsured deposits are almost always bailed out in the model—in line with the empirical evidence in Section 2.2—so that protecting them further has only limited benefits.

Moving to the optimal policy produces small effects on macroeconomic variables. GDP, employment, investments, and consumption change by 0.01% or less, when comparing the new stochastic steady state with the initial one. Nonetheless, the stock of "runnable" liabilities (i.e., uninsured deposits) drops by 88%, and the bank default rate drops by about 9 bps (from an average of 64 bps, that is, by 14%) because fewer banks are subject to runs.

[22]The $525,000 limit is computed using the full set of rules of the FDIC, that is, assuming that this limit applies per depositor, per bank, and per ownership category. See section 6 for a discussion of these rules.



(a) Firm Insurance ϕ^f (b) Household Insurance ϕ^h

Figure 6. Optimal Deposit Insurance

The figure plots household welfare as a function of the level of deposit insurance ϕ^f for firms' deposits (left panel) and households' deposits ϕ^h (right panel), in the baseline model with the working capital constraint given by (5). Each plot is constructed by fixing the level of insurance of the other group at the welfare-maximizing level. Welfare is expressed in consumption equivalent units relative to the baseline. In both plots, the dotted line reports welfare for a model without bank runs ($\pi = 0$) and the model is recalibrated to match all other targets, and the solid line plots welfare for the full model in which there are bank runs.

A key quantitative benefit of deposit insurance is to reduce runs. Figure 6 shows that the welfare effect of changing deposit insurance are even smaller without bank runs (reported as dotted lines). The optimal insurance for households' deposits drops to zero in an economy without runs, but it remains optimal to provide 100% insurance to firms' deposits.

While the welfare gains of the optimal policy are small, eliminating government guarantees generates large welfare losses, as shown in Table 3. In the baseline model with the working capital constraint given by (5), removing deposit insurance, bailouts, or both produces a welfare loss of 3, 11, or 42 bps, respectively. The effects are even bigger when the working capital constraint is given by (32), so that bank default leads to additional liquidity losses for firms—up to 5% of annual consumption, when all government guarantees are removed.

These results speak to the role of current FDIC policies in ensuring financial stability. As noted at the end of Section 2.2, banks that acquire a failed institution can either purchase all of the uninsured deposits at face value, or only the insured deposits, and there is no intermediate resolution method in which the uninsured deposits are transferred to the acquiring bank after

Policy	Parameter	Welfare (consumption equivalent, %)	
		Baseline, eqn (5)	Alternate, eqn (32)
No deposit insurance	$\phi^f = \phi^h = 0$	-0.03	-0.03
No bailout	$f = 0$	-0.11	-1.09
No deposit insurance and no bailouts	$\phi^f = \phi^h = f = 0$	-0.42	-5.00

Table 3. Welfare Costs of Reducing Coverage

The table reports the welfare losses, in consumption equivalent % units relative to the baseline, of eliminating various forms of government guarantees.

imposing a haircut. Our model estimates suggest that allowing for such an intermediate approach—corresponding to a reduction in f in the model—would lead to large welfare losses. Indeed, most of the welfare benefits of the current setting come from the fact that uninsured deposits rarely experience losses, rather than the explicit deposit insurance itself.

5.3 Robustness

In this section we analyze the robustness of both of our counterfactual results; specifically, the effect on GDP of reducing the bailout probability f, and the optimal level of deposit insurance for firms and households. For each robustness exercise, we recalibrate the model to match our data targets as discussed in Section 4.

The main results of the previous sections are robust to various extensions of the model; in particular, insuring 100% of firms' deposits remains optimal in all our robustness exercises. Table 4 lists the results. Each row is a separate extension to the model, and for each extension, we separately consider the baseline model where bank failure affects only deposits (first three columns) using the working capital constraint (5), and the extension where bank failure affects all sources of firms' liquidity (second set of three columns) using the alternate working capital constraint (32).

First, we account for the fact that firms hold other liquid assets in addition to deposits. We augment the model so that each firm can invest its assets a_t^i in capital k_t^i, deposits d_t^i, and other liquid assets s_t^i, so that the budget constraint (3) becomes $k_t^i + d_t^i + s_t^i \leq a_t^i$. The other liquid assets pay a gross return R_t^s and provide some liquidity to finance wages. Specifically, the working capital constraint becomes

$$w_{t+1} l_{t+1}^i \leq \hat{R}_{t+1}^d d_t^i + \zeta^s R_t^s s_t^i + \bar{\theta} y_{t+1}^i, \tag{33}$$

where ζ^s parameterizes the liquidity provided by the other liquid assets. We calibrate ζ^s to obtain

Model	Baseline, equation (5)			Alternate, equation (32)		
	ΔGDP	Firm	Household	ΔGDP	Firm	Household
Baseline	-0.07%	100%	87.7%	-1.18%	100%	94.9%
Other Liquid Assets	-0.07%	100%	87.2%	-1.20%	100%	94.8%
Negative Equity	-0.07%	100%	88.6%	-1.06%	100%	95.5%
Early Withdrawals	-0.07%	100%	92.3%	-0.90%	100%	97.4%
More Deadweight Loss	-0.11%	100%	94.8%	-1.21%	100%	98.7%
Bad Risk-Taking	-0.17%	100%	46.2%	-1.38%	100%	51.3%

Table 4. Robustness

The table reports the main results of the counterfactual analyses for various extensions of the model. The first three columns report the percent change in GDP when reducing the bailout probability, the optimal deposit insurance for firms ϕ^f, and the optimal deposit insurance for households ϕ^h, respectively, for the baseline model with working capital constraint (5). The second set of three columns report the same values for the model in which firms lose all liquidity when their bank fails (i.e., the working capital constraint is given by (32)). The first row reports the baseline optimal policy, and each of the other rows report the results of an extension: allowing firms to use liquid assets other than deposits to pay for wage (second line); allowing banks with negative equity to operate for some time (line three); allowing a fraction of depositors to withdraw all their uninsured deposits in the event of a run (line four); increasing deadweight losses of default (line five); and introducing risk-shifting (Jensen and Meckling, 1976) using the bad risk-taking approach of Pancost and Robatto (2023) (line six).

a 0.13% liquidity premium on other liquid assets (i.e., the average spread between the rate on a risk-free illiquid asset and R_t^s), which we compute by using the approach of Krishnamurthy and Vissing-Jorgensen (2012) and extending their sample up to 2019. We set the supply of other liquid assets to 5.25% of GDP by considering firms' holdings of a broad set of other liquid assets: Treasury securities, money market funds, reverse repos, commercial paper munis, and agency securities.[23] Table 4 shows that the results are essentially identical to those of our baseline model.

Second, we extend the banks' problem so that banks with negative equity can operate for some time, rather than being immediately shut down as in the baseline model. This extension is motivated by the numerous instances of banks that kept operating during both the Savings & Loans crisis and the 2023 banking crisis despite having negative net worth based on mark-to-market accounting (FDIC 1997, Chapter 4; Jiang et al. 2023; Begenau, Elenev and Landvoigt 2024). This is the result of various regulations that allow banks to report the book value of their held-to-maturity loans (Jiang et al., 2023), to use historical cost accounting when valuing held-to-maturity and, for some banks, even available-for-sale securities (Kim, Kim and Ryan, 2019), and to delay the recognition of losses on their loans (Begenau et al., 2021). Appendix H provides the details of this extension,

[23] We consider the average between 2001 and the end of our sample in 2019 because of a trend in the initial part of the sample.

and Table 4 shows that the results are again unchanged.

In a second extension, we allow depositors to withdraw a fraction κ of deposits from failing banks—both those that are fundamentally insolvent and those subject to runs—before the banks are taken over and shut down by the government. We set $\kappa = 0.25$ based on the evidence of Martin, Puri and Ufier (2018), which is also consistent with the withdrawals during the run on SVB (Federal Reserve Board of Governors, 2023). Allowing partial withdrawals also mitigates the drop in GDP when we reduce the bailout probability f, for the model in which firms lose access to all of their liquidity in the event of bank failure (equation 32). However, the haircut on the fraction of deposits that are not withdrawn increases, and thus, it is optimal to have a higher level of deposit insurance for households to further reduce the risk of runs.

Next, we consider the effects of increasing the deadweight losses of default. These losses are likely higher in crises times—when many banks fail at the same time—possibly because buyers of failed banks are constrained (Granja, Matvos and Seru 2017; Acharya and Yorulmazer 2008). The evidence in Bennett and Unal (2014) and Granja, Matvos and Seru (2017) show that resolution costs increase by about 3 percentage points during crises.[24] To provide a simple and transparent result, we increase the deadweight loss of default Υ^{dwl} at all times by 3 percentage points—this provide an upper bound of the effects. Not surprisingly, the optimal deposit insurance for households is higher, but the broad results are unchanged.

Finally, we consider an extension in which banks can risk-shift (Jensen and Meckling, 1976). Absent moral hazard on the side of banks, 100% deposit insurance would be optimal; in our baseline model, the moral hazard leads banks to grow too large, generating an inefficient overaccumulation of physical capital in the economy. In the extension, we build on the "bad risk-taking" of Pancost and Robatto (2023) and allow banks to invest in a technology that increases their idiosyncratic risk, at a cost. Although banks find this technology profitable—because they reap the profits if the gamble pays off but leave the losses to the deposit insurer if it fails—the technology itself creates no value and is negative NPV. Appendix G provides details about the extension. We calibrate the extension assuming that 87% of bank failures due to fundamentals are attributable to bad risk-taking (Pancost and Robatto, 2023, Table 3); such a large degree of moral hazard generates large benefits of reducing deposit insurance, so that depositors "discipline" banks' risk-taking decisions, and the results provide a lower bound on our estimate of the optimal deposit insurance. Not

[24] In particular, Granja, Matvos and Seru (2017) report that the average cost of resolving failed banks between 2007 and 2013 is 28% of assets, but only 25% if acquirers are better capitalized. The difference between the two figures is 3 percentage points.

surprisingly, the optimal degree of deposit insurance drop substantially for households, but it remains optimal to insure 100% of firms' deposits.

6 Effective Deposit Insurance Coverage

In this section, we provide an example to illustrate how our estimates of households' insured and uninsured deposits from the SCF (Section 2.1) can be used in additional analyses, beyond guiding the design and calibration of quantitative models. We show that households are able to increase the *effective insurance* on their deposits by about 50% relative to the limit by exploiting various FDIC rules, and that simplifying the system of *ownership categories* used in determining insurance coverage would not substantially affect the level of insurance coverage, contrary to the concern expressed by the FDIC (FDIC, 2023).

The FDIC provides insurance up to $250,000 *per depositor*, *per bank*, and *per ownership category*. The qualifiers *per depositor* and *per bank* are rather straightforward.[25] The qualifier *ownership category* is particularly relevant for households, who obtain separate insurance for deposits in single accounts, joint accounts, trust accounts, and certain retirement accounts separately. To give a simple example, consider a depositor with a checking account and an individual retirement account (IRA). The depositor enjoys insurance up to $250,000 on the checking account and up to $250,000 on the IRA because the two accounts are in different ownership categories.[26]

Figure 7 shows that households' average effective deposit insurance coverage is about 50% higher than the statutory limit. The solid line represents the statutory FDIC limit per bank, depositor, and ownership category. The dashed line plots the estimated average *effective deposit insurance coverage* for household members with positive holdings of uninsured deposits. The dotted line in Figure 7 shows the effective limit calculated by ignoring the distinction between ownership categories is nearly identical to the one calculated using the FDIC rules. Hence, households achieve higher effective insurance coverage mainly by holding accounts at multiple banks.

The result has implications for the reform and simplification of deposit insurance. The FDIC notes that reducing the number of ownership categories would simplify the resolution process, but raises the concern that such reduction would limit the effective insurance for households (FDIC, 2023). Our results suggest that this concern is not quantitatively relevant.

[25] For instance, a depositor can insure up to $500,000 by splitting her deposits across two banks.

[26] Unlike households, firms are effectively limited to $250,000 in coverage per bank because they generally have a single ownership category. Of course, firms can—like households—increase their effective deposit insurance coverage by holding deposits at multiple banks.

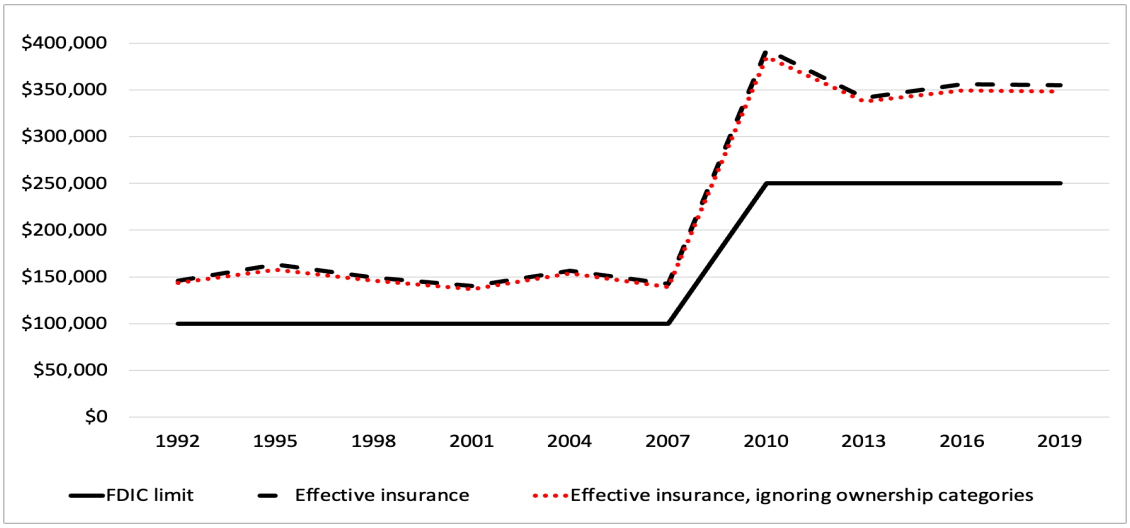


Figure 7. Deposit insurance limit.
The figure displays the FDIC insurance limit, the effective insurance limit for households (calculated as the average amount of insured deposits for household members with positive holdings of uninsured deposits), and the effective insurance limit for households computed by ignoring the ownership categories.

7 Conclusion

We document novel stylized facts about households' and firms' holdings of insured and uninsured deposits and the losses on uninsured deposits at failed banks. First, firms hold more uninsured deposits than households, and second, uninsured deposits rarely suffer losses when a bank fails.

We then design and calibrate a quantitative general equilibrium model around these facts to analyze the effects of changing deposit insurance and bailouts. First, reducing the bailout probability produces small effects on the economy, unless bank failures affect not only firms' deposits but also other sources of firms' liquidity, such as credit lines. Second, a *targeted coverage* policy maximizes welfare, that is, the optimal deposit insurance policy involves 100% coverage for firms' deposits but only partial coverage for households' deposits. However, the welfare gains from implementing this policy are small because the current FDIC approach of resolving failed banks, which rarely imposes losses on deposits, is already close to full insurance.

Our paper opens up several directions for future research. On the empirical side, our estimation of firms' and households' insured and uninsured deposits can be used for other analysis besides calibrating structural models—we provide an example that speaks about the FDIC's proposal to simplify the system of *ownership categories*. On the theoretical side, open questions remain about the optimal joint design of the deposit insurance scheme and the resolution of failed banks.

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Appendix

A Deposits and bank failures data analysis: details

A.1 Deposits

We use the Survey of Consumer Finances (SCF) to compute the amount of deposits held by households and to break this quantity down into insured and uninsured deposits. For other groups of depositors, we obtain aggregate data from the Flow of Funds (FF). When we work with both the SCF and FF at the same time, we use FF data from the third quarter of the respective year to facilitate the comparison. In the rest of this subsection, we provide details about our data analysis using the SCF. Starting with the 1992 survey, the SCF asks each respondent to provide detailed information about checking accounts, saving accounts, money market accounts, and certificate of deposits.

Regarding checking accounts, all years include information about amount, bank, and ownership of six checking accounts, as well as the amount held in any remaining checking account. We lack information about the bank and ownership of the remaining checking accounts, so we assume that the amount in these accounts is held in one bank (that is different from all the other banks the household is engaged with) and is owned by the respondent.

Between 1992 and 2001, the SCF asks respondents about their money market deposit accounts, but this information is combined with savings accounts after 2001. Specifically, between 1992 and 2001, the survey asks about amount, bank, and ownership of up to three money market deposit accounts, as well as any amount held in additional money market deposit accounts. Similar to checking accounts, we assume that the amount held in additional accounts is in one bank (that is different from all the other banks with which the household is engaged) and is owned by the respondent.

Regarding savings accounts, the SCF asks about amount, bank, and ownership of up to five savings accounts between 1992 and 2001, and up to six savings/money market accounts after 2001. Similar to checking accounts, the SCF also asks about the amount held in any remaining checking account, and we assume such an amount is held in one bank (that is different from all the other banks with which the household is engaged) and is owned by the respondent.

Regarding certificate of deposits (CDs), the SCF provides the total amount of all CDs held by the family, up to five institutions where the CDs are held in the 1992 survey and up to seven in

the following ones, and one response about the ownership of all the CDs. If the respondent lists multiple institutions where the CDs are held, we assume that the household owns the same amount of CDs at each of the institutions that are listed.

When information about the bank is provided, the public version of the SCF contains an identifier of the bank (rather than the name) for up to seven financial institutions with which the household is engaged. For each additional institution, we have information about the broad category of the institution (e.g. "commercial bank," "brokerage," "person or other non-institution,"...). We remove accounts held at non-bank institutions such as stores, insurance companies, churches, unions, etc.

When information about ownership is provided, each account is assigned one of the following options: respondent, spouse, child or grandchild, other family member, unrelated person, respondent and spouse, respondent/spouse and child/grandchild, respondent/spouse and other relative, and respondent/spouse and unrelated person. We treat "child/grandchild" as one single owner. For joint ownership, we assume that the account is owned by three people; for instance, if the ownership is recorded as "respondent/spouse and child/grandchild," we assign equal ownership to the respondent, the spouse, and the child/grandchild. The SCF question about ownership includes, as possible responses, also "personal business account" and "trust account." We exclude personal business accounts, and we use the "trust account" to compute holdings in the trust ownership category (see Section 6 for a discussion of ownership categories). We assign the ownership of trust accounts entirely to the respondent.

We then calculate the amount held by each owner in any given bank, distinguishing between three ownership categories: single accounts, joint accounts, and (only for the respondent) trust accounts. Finally, we compute the amount of uninsured deposits, if any, as those that exceeds the FDIC insurance limit for each depositor, bank, and ownership category.

A.2 Bank failures

We use FDIC data to construct our sample of failed banks. We exclude banks for which the FDIC bore no resolution cost, those for which the resolution cost is not available, or those that are recorded to have a negative resolution cost. Finally, we exclude banks for which data about assets or deposits as of the last filed Call Report before failure are not available.

For each failed bank, we then determine whether uninsured deposits experienced losses, based on the resolution method used by the FDIC. We drop 16 observations categorized as "MGR" (i.e.,

in which the resolution was handled by the Federal Savings and Loan Insurance Corporation by taking over management and generally providing financial assistance) because we cannot determine if uninsured deposits experienced losses. In our sample, uninsured depositors experienced no losses if the bank is resolved with a purchase and assumption transaction or if it is an assisted transaction, and experience losses in all other cases.

B Approximate Firm Size Distribution

Here we provide more details about the approach we use to measure the firm size distribution in the model and in the data. Because the model allows for aggregation and a representative firm, the firm size distribution has no direct impact on any endogenous variables. However, we use the endogenous firm size distribution as a way to calibrate the model parameters; in particular, we pick p_z and z^H to match the observed Pareto tails of the firm size distribution of both incumbents firms and all firms, as described in Section 4.

We specify a grid of N values of firm assets $\{\bar{a}_j\}_{j=1}^N$, and denote the unconditional probability that a firm has assets equal to $\bar{a}_j$ at time t as g_t^j. For convenience, we denote the $N \times 1$ vector of all values of g_t^j as $\vec{g}_t$. In addition, we require two other firm size distributions: we assume that the size distribution of entering firms (with total resources equal to a_t^{entry}) is given by an exogenous distribution $\vec{g}^e$ which is constant over time, and that the endogenous distribution of incumbent firms at t, who have received the aggregate and idiosyncratic shocks but have not yet received the exit shocks, is given by $\vec{g}_t^i$.

The total mass of incumbents in the economy at time t is given by m_t^i, and the mass of entrants is given by m_t^e. The total mass of incumbents is governed by households' choice of a_t^{entry}; in particular, $a_t^{entry} = m_t^e \bar{a}^{entrant}$, where $\bar{a}^{entrant}$ is the average entrant size according to the distribution $\vec{g}^e$. Then the mass of incumbents at t is $m_t^i = \left(1 - p^{exit}\right) m_{t-1}^i + m_t^e$. Given these dynamics, the law of motion for the endogenous firm size distribution $\vec{g}_t$ is given by

$$\vec{g}_t = \frac{\left(1 - p^{exit}\right) m_{t-1}^i f_t\left(\vec{g}_{t-1}\right) + m_{t-1}^e \vec{g}^e}{\left(1 - p^{exit}\right) m_{t-1}^i + m_{t-1}^e},$$

where $\vec{g}_t^i = f_t\left(\vec{g}_{t-1}\right)$ is the endogenous distribution of size among incumbent firms, and $f_t(\cdot)$ is the time-varying function that applies the aggregate and idiosyncratic shocks, and firm's labor and investment decisions, to firm assets.

We approximate f_t as follows. First, let $\vec{R}_t$ be the 4×1 vector of endogenous returns on firm assets, corresponding to the four idiosyncratic states the firm can experience: productivity of z^H or z^L, and either their bank survives or fails. Similarly, let $\vec{p}_t$ be the 4×1 vector of the associated probability of each shock. Both $\vec{R}_t$ and $\vec{p}_t$ will vary over time; the former varies with the aggregate shock A_t, and as firms make different labor and investment choices, while the latter varies with the endogenous probability of bank failure p_t.

Given the two 4×1 vectors $\vec{R}_t$ and $\vec{p}_t$, and the $N \times 1$ grid of values of $\bar{a}$, there are $4N$ possible values for incumbent assets $\tilde{a}_t$, with associated probability $\tilde{p}_t$:

$$\begin{aligned}\tilde{a}_t &= \bar{a} \otimes \vec{R}_t \\ \tilde{p}_t &= \vec{g}_{t-1} \otimes \vec{p}_t,\end{aligned}$$

where $\bar{a}$ is the $N \times 1$ vector of assets values in the grid.

The approximation of f_t requires us to reduce the $4N \times 1$ vector $\tilde{p}_t$ of probabilities down to an $N \times 1$ vector that lies on the $\bar{a}$ grid. To do so, we allocate the mass at each of the $4N$ points in the endogenous $\tilde{a}_t$ grid, to the smaller $\bar{a}$ grid, according to how close each value is to the two nearest points in $\bar{a}$. In particular, for each $k = 1, 2, ...4N$ we compute

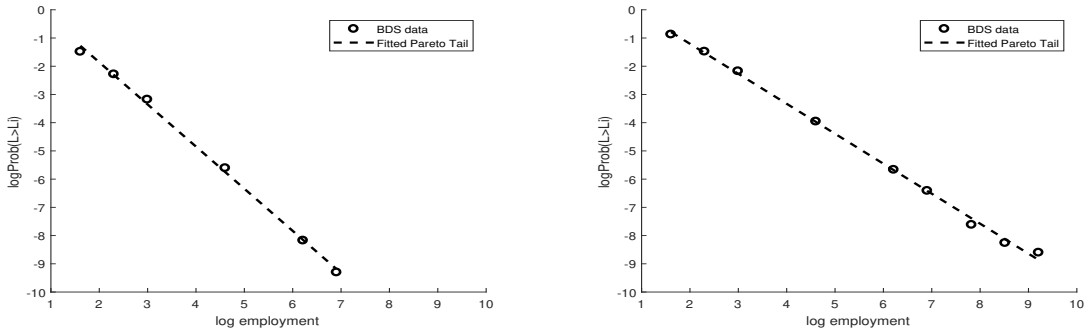
$$t_k \equiv \begin{cases} 1 & \text{if } \tilde{a}_t^k < \bar{a}_1 \\ \frac{\bar{a}_{j(k)+1} - \tilde{a}_t^k}{\bar{a}_{j(k)+1} - \bar{a}_{j(k)}} & \text{if } \tilde{a}_t^k \in [\bar{a}_1, \bar{a}_N] \\ 0 & \text{if } \tilde{a}_t^k > \bar{a}_N \end{cases}$$

where $j(k)$ denotes the smallest value of j such that $\tilde{a}_t^k > \bar{a}_j$, and where values above $\bar{a}_N$ and below $\bar{a}_1$ are truncated to $\bar{a}_N$ and $\bar{a}_1$, respectively. We then use $\{t_k\}_{k=1}^{4N}$ to allocate the $4N$ values of $\tilde{a}_t$ to the N spots on the $\bar{a}$ grid according to

$$\begin{aligned} g_t^{j(k)} &= t_k \tilde{p}_t^k \\ g_t^{j(k)+1} &= (1 - t_k)\, \tilde{p}_t^k \end{aligned}$$

for all k from 1 to $4N$.

To implement this procedure, we assume that $\log \bar{a}_i$ takes $N = 10$ uniformly-spaced values between 1 and $\log(100,000)$. Given a time series of the two endogenous size distributions $\vec{g}_t$ and $\vec{g}_t^i$, we calculate the implied Pareto tail for each as the slope coefficient from regressing $\log \Pr\{a > \bar{a}_i\}$



(a) Entrants (b) All Firms

Figure 8. Pareto Tail Indices

Both panels plots the probability mass of observing firms with employment greater than or equal to the value on the x-axis in the Census Business Dynamic Statistics data as circles, and a fitted regression line as a dotted line. The left panel plots values for entrants, defined as firms that are at most one year old, while the right panel plots values across all firms. The implied slopes are -1.49 and -1.06, respectively.

on $\log \bar{a}_i$.

We calculate the data values for the two Pareto tail coefficients using the Business Dynamic Statistics (BDS) of the US Census Bureau. While the BDS does not report firm assets, it does report employment, which is proportional to assets in our model. On average from 1978 to 2021, the Pareto tail for all firms is 1.062, while that for firms that are 1 year or older is 1.054; we calibrate z^H and p_z to match these two moments. The implied Pareto tail for entrants in the data is 1.494, and in addition 77% of entrants are in the lowest size category (1–4 employees), both of which we use to calibrate $\vec{g}^e$.

The top panel of Figure 8 plots the log anti-CDF against log employment from the BDS data for entrant firms, against the fitted regression line. The implied slope of -1.49 in the figure is not driven by any one size category, and is a robust feature of the data. The bottom panel repeats the exercise for all firms; the implied slope of -1.062 is one of our calibration targets.

C Calibrating the sunspot probability π: details

As described in Section 4, we calibrate the sunspot probability π by matching the 3.8% bank default rate in the 1921-1933 pre-FDIC period when we shut down deposit insurance and the bailouts of uninsured deposits (i.e., setting $f = \phi^f = \phi^h = 0$). In this exercise, to better align the model to the conditions in the banking system in 1921-1933, we make two modifications.

First, we set the capital requirement parameter ζ to 13% to match the capital-asset ratio of national banks for that period (Figure 3 in Tufts and Moloney, 2022). Even if formal capital requirements were not in place at that time, banking laws required banks to have a minimum amount of capital in dollar terms, and Tufts and Moloney (2022) suggest that this constraint was binding, at least for some of the pre-FDIC years.

Second, we extend the model to account for the fact that at this time, bank equity-holders faced double liability, rather than the limited liability they enjoy today. In particular, in the event of bank failure bank shareholders would not only lose the amount they invested, but also for an additional amount equal to their investment. However, Tufts and Tufts (2021) and Marquis and Smith (1937) document that in practice the actual additional liability was closer to 29% of the capital of failed banks. Thus, we extend the model so that shareholders set aside additional resources amounting to 29% of equity, invested at the risk-free rate R_t^f, and these resources are used if the banks' assets are not enough to repay depositors. We continue to refer to this extension as double liability, even if shareholders are actually liable for only 1.29 times their investment.

More formally, when modeling the double liability, a bank is set up with equity $1.29 \times n_t$, and the additional 29% of resources is set aside and invested at the risk-free rate R_t^f. The problem of banks, (9), becomes

$$\max_{b_t,\, d_t} \; E_t \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ \varepsilon b_t \left(1 - \delta + r_t\right) + 0.29\; n_t R_t^f - R_t^d d_t \right\} dF_{t+1}\left(\varepsilon\right),$$

subject to the same budget and capital requirement constraints as in the baseline, that is, (10) and (11). The return on banks' investments is now given by

$$R_{t+1}^n = \frac{1}{n_t(1+29\%)} \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ \varepsilon b_t \left(1 - \delta + r_t\right) + 0.29\; n_t R_t^f - R_t^d d_t \right\} dF_{t+1}\left(\varepsilon\right).$$

We also modify the thresholds $\underline{\varepsilon}_{t+1}^{FUN}$ and $\underline{\varepsilon}_{t+1}^{RUN}$. The fundamental insolvency threshold is defined so that a bank fails if its assets (including the extra 29% of equity) are not enough to pay liabilities:

$$\underline{\varepsilon}_{t+1}^{FUN} b_t(1 - \delta + r_t) + 0.29\; n_t R_t^f = R_t^d d_t.$$

To redefine the run threshold, we assume that the resources $0.29\; n_t R_t^f$ are not available to pay depositors during a run—consistent with the view that it took time to recover these resources from shareholders (Tufts and Tufts, 2021). Thus, the run threshold $\underline{\varepsilon}_{t+1}^{RUN}$ is now defined by the

expression

$$\underline{\varepsilon}_{t+1}^{RUN} \, b_t \left(1 - \delta + r_t\right) + 0.29 \, n_t R_t^f = \frac{R_t^d d_t^{uns}}{1 - \Upsilon^{tot}}. \tag{34}$$

That is, as in the baseline model, the bank has to liquidate assets at a fire-sale cost to repay the depositors that run on the bank. Note also that we have omitted the insured deposits d_t^{ins} from (34) because we are using (34) only in a version of the model with no deposit insurance.

Finally, the haircut on deposits ν_{t+1} is now defined by the expression

$$\int_{\varepsilon \in \mathcal{E}_{t+1}} R_t^d d_t^{uns} \left(1 - \nu_{t+1}\right) dF_{t+1}\left(\varepsilon\right) = \int_{\varepsilon \in \mathcal{E}_{t+1}} \left[\varepsilon \, b_t \left(1 - \delta + r_t\right) \left(1 - \Upsilon^{tot}\right) + 0.29 \, n_t R_t^f\right] dF_{t+1}\left(\varepsilon\right),$$

to account for the extra resources that are available because of the double liability, and omitting d_t^{ins} similar to (34).

D Calibration: additional details

In this appendix, we describe how we calibrate some of the parameters listed in Panel B of Table 2, and we describe the data we use to compute the data moments. For most of these moments, we follow the approach of Pancost and Robatto (2023) and extend their data sample up to 2019.

The parameters that govern banks' idiosyncratic risk (i.e., $\bar{\sigma}$, σ_σ, and ρ_σ) are disciplined using bank default rates, measured as the banks that fail (weighted by assets) and for which the FDIC incurred a positive resolution cost.

The parameters θ, ξ, and ψ govern the liquidity premium and the stock of firms' and households' deposits relative to GDP. In the data, we measure the liquidity premium as the difference between the rate on 3-month AA commercial paper, which proxies safe illiquid assets as in Davydiuk (2019) and Pancost and Robatto (2023), and the rate paid by banks on deposits. Both the commercial paper and deposit rates in the data are computed first at a quarterly frequency, and from that, we calculate the average liquidity premium in our sample.

Regarding commercial paper rates, we follow Davydiuk (2019) and use the three-month AA commercial paper rate for January 1986-August 1997 (FRED series CP3M) and the average rate on three-month AA financial and nonfinancial commercial paper for the rest of the sample (FRED series CPN3M and CPF3M).

The interest rate on deposits is measured as the ratio of interest expense on domestic deposits relative to the stock of such deposits, using FDIC data. We compute the ratio between expenses

on deposits in domestic offices divided by the amount of deposits in domestic offices at the end of the previous quarters.

We calibrate σ_A, ω, σ_ξ, and $\rho_{A,\xi}$ to match the second moments of some macroeconomic and financial variables: the volatility of GDP, labor, and firms' deposits, and the correlation between GDP and deposits, respectively. Real GDP is from FRED (series GDPC1). Labor is measured as one minus the unemployment rate (FRED series UNRATE). For total deposits, we use domestic deposits at FDIC-insured banks—note that households' deposits from the SCF are available only every three years, but to discipline second moments, we need data at a higher frequency.

E Untargeted Moments

In this section we validate the model by comparing model-implied moments to the data. In particular, the moments discussed here were not used to calibrate the model parameters reported in Table 2. We provide a list of untargeted moments in Table 5 for both the data and the model.

The model matches well business cycle moments such as the volatilities of investment and consumption, and the correlation of GDP with investment, consumption, and labor. Regarding wages, the model's volatility is somewhat lower than in the data, and the correlation with GDP somewhat higher.

In terms of banking moments, the model matches well the ratio of bank assets to GDP and the ratio of bank assets to the stock of capital—the latter is measured as nonfinancial assets of nonfinancial firms. It also matches reasonably well the volatilities of bank assets and deposits, though the correlations of GDP with bank assets and deposits are somewhat low. The model does not match either the volatility or the correlation with GDP of the deposit premium, though this is a common feature of macro-banking models (Davydiuk, 2019; Pancost and Robatto, 2023). The model produces a negative correlation between bank default and GDP growth, similar to the data. While the magnitude in the model is smaller than in the data, we note that the correlation in the data is not statistically different from zero, and thus, the performance of the model in this regard is good.

The model matches almost exactly the average haircut on deposits at failed banks. In the model, this is the haircut ν_t that would be applied to the deposits at all failed banks absent government interventions. At nearly all such banks, uninsured deposits are bailed out, and thus, the losses are borne by the government. In the data, we restrict attention to the bank failures with no losses on

uninsured deposits—which are again the great majority—and compute the haircut as the average ratio of the costs to the insurance fund relative to the assets of the failed banks.

Finally, we report some moments related to the firm size distribution. Recall that the process for the firms' idiosyncratic shocks z_t^i is calibrated to match the Pareto tail coefficient of the entire firm-size distribution (see Section 4 and Appendix B). The last two lines of Table 5 show that the model also matches the data when we restrict attention to the right-tail of the distribution. The top 10% of firms account for 76% of aggregate employment in the data and 78% in the model. Going further into the right tail, the top 1% of firms make up about 52% of employment in the data and 57% in the model. To compute these values, we use the average values of employment in each bin in the BDS data and the corresponding object in the model, that is, the $\log \bar{a}$ grid-points (see Appendix B). Because neither the BDS bins, nor the $\log \bar{a}$ points, land on precisely 10% and 1% of firms, we linearly interpolate between the two closest grid-points in each case.

F Extension: A Model with Credit Lines

In this appendix, we present an extension of the model in which firms use two sources of bank liquidity to finance their wage payments: deposits and credit lines. The model produces results that are similar to those of the model in the main part of the paper in which the working capital constraint is given by (32), described in Section 5.1.2. That is, when bank defaults trigger not only losses on deposits but also on other sources of liquidity, the macroeconomic effects are large. In addition, the result about the optimality of 100% deposit insurance for firms and lower deposit insurance for households is robust to adding credit lines. Relative to the structural banking model with credit lines in Choi (2022), the focus here is on how bank failures reduce the liquidity available to firms if credit lines becomes available, as opposed to how extending credit lines exposes banks to firms' risk as in Choi (2022).

F.1 Firms

At time t, firm i and its bank establish a line of credit that allows the firm to borrow liquidity at $t+1$ to finance its wages. We assume that the committed line of credit cannot exceed a fraction θ of the expected output that firm i will be able to produce, conditional on receiving the high

Moment	Data	Model
Volatilities, ratios to volatility of log GDP, HP-filtered		
log(investment)	4.23	3.42
log(consumption)	0.68	0.49
log(wages)	0.84	0.46
log(bank assets)	2.29	1.52
log(deposits)	1.83	1.51
log(1 + deposit premium)	0.66	0.01
Correlations with log GDP, HP-filtered		
log(investment)	0.94	0.86
log(consumption)	0.80	0.71
log(labor)	0.85	0.90
log(wages)	0.44	0.74
log(bank assets)	0.67	0.33
log(1 + deposit premium)	0.70	0.14
log(firm deposits)	0.71	0.14
Other Moments, not HP-filtered		
Corr(bank default rate, $\Delta \log$ GDP)	-0.13	-0.004
Bank assets, share of capital stock	0.24	0.19
Bank assets, share of GDP	0.41	0.43
Haircut on deposits at failed banks	17%	16%
% of employment, top 10% of firms	76%	78%
% of employment, top 1% of firms	52%	57%

Table 5. Untargeted Moments

The table reports values of untargeted moments for both the data (second column) and the model (third column). The top panel reports volatility moments as a ratio to the volatility of log GDP. The middle panel reports correlations with log GDP. The bottom panel reports other moments. All moments in the top and middle panels are computed by applying the HP-filter both to the data and model-simulated series, using a smoothing parameter of 100.

idiosyncratic productivity shock z^H:[27]

$$\varphi_t^i \leq \theta \mathbb{E}_t \left\{ y_{t+1}^i | z_{t+1}^i = z^H \right\}. \tag{35}$$

Thus, relative to the baseline model, the credit line formalizes the sources of liquidity that firms are able to obtain by pledging the revenues obtained from selling their products. The interest payment on the amount that is drawn down is r_t^{φ}.

[27] Formally, the parameter θ limit firms' ability to pledge the cash flow produced by selling its good. To make sure that firms do not borrow more than what they can pledge, we can assume that the line of credit includes a covenant that allows the bank to reduce the size of the line of credit at $t+1$ if the firm is hit by the idiosyncratic shock z^L. This approach is consistent with the way credit lines are set in practice (Greenwald, Krainer and Paul 2023).

Crucially, a firm might be unable to draw down its credit lines in $t+1$ if its bank fails. Specifically, we assume that the firm has no access to the credit line at $t+1$ if (i) its bank fails and (ii) the uninsured deposits are not bailed out. This is consistent with what happens in practice. The most common case in which uninsured deposits are not bailed out is when the FDIC takes over a failing bank and starts the liquidation process—either because it received no bids from other financial institution to buy the failed bank, or because liquidation is the cheapest option for taxpayers (see the discussion in Section 2.2). In this case, the FDIC takes actions to preserve the value of the bank, which "generally precludes continuing the lending operations of a failed bank".[28] If instead the failed bank is sold to another one—the most common case in which uninsured deposits do not experience losses—the operations of the failed bank typically continue normally.

The working capital constraint (5) thus becomes

$$w_{t+1}l_{t+1}^i \leq \begin{cases} R_t^d d_t^i + \varphi_t^i & \text{w/prob. } p_t^{full} \text{ (i.e. if deposits are fully repaid)} \\ R_t^d d_t^i \left[\phi^f + \left(1-\phi^f\right)\nu_{t+1}\right] & \text{w/prob. } 1-p_t^{full}, \end{cases} \tag{36}$$

which is essentially the same as the working capital constraint in (32), that is, the version of the model in the main part of the paper in which the firms' ability to pledge their cash flow drops to zero for firms that face losses on their uninsured deposits.[29]

After production, the total amount of resources available to the firm is

$$a_{t+1}^i = \begin{cases} y_{t+1}^i + (1-\delta)\, z_{t+1}^i k_t^i + \hat{R}_{t+1}^d d_t^i - w_{t+1}l_{t+1}^i - r_t b_t^i - r_t^\varphi \varphi_t^i & \text{if the credit line is drawn down} \\ y_{t+1}^i + (1-\delta)\, z_{t+1}^i k_t^i + \hat{R}_{t+1}^d d_t^i - w_{t+1}l_{t+1}^i - r_t b_t^i & \text{otherwise} \end{cases}$$

where $\hat{R}_{t+1}^d$ is the realized return on deposits defined in Equation (2).

The rest of the firms' building block of the model is unchanged. To solve the model, we conjecture—and then verify after solving the model—that among the firms with no losses on uninsured deposits, only firms hit by the high idiosyncratic shock z^H draw down their credit line in $t+1$. We also conjecture that firms' demand at time-t for the credit line φ_t^i is constrained by (35)—so that (35) holds with equality—and we verify this is the case after solving the model.

[28] See https://www.fdic.gov/resources/resolutions/bank-failures/failed-bank-list/borrowers/.

[29] Formally, there is a small difference in that in the main part of the paper, liquidity obtained from pledging revenue is $\bar{\theta} y_{t+1}^i$, which is measurable with respect to the time-$t+1$ aggregate state, whereas here the credit line φ_t^i is only measurable with respect to time t. This difference allows us to more easily model the credit lines in the banking problem, and it has small effects on the quantitative predictions.

F.2 Banks

We continue to assume that banks are founded each period t with equity n_t, borrow deposits d_t from firms and households, and provide (term) loans b_t to firms at time t. They now also commit to provide liquidity at $t+1$ to firms for an amount φ_t. Because we conjectured, in the previous section, that only firms hit by the shock $z^i_{t+1} = z^H$ draw the credit line down in $t+1$, the actual amount borrowed through credit lines is $p^z \varphi_t$—recall that p_z is the probability that $z^i_{t+1} = z^H$, and because of the law of large numbers, also the fraction of firms with $z^i_{t+1} = z^H$.

As in the baseline model, the revenues from term loans are $\varepsilon b_t(1 - \delta + r_t)$. The revenues from credit lines are hit by the idiosyncratic bank shock ε, similar to those of terms loans, and are thus given by $\varepsilon p_z \varphi_t (1 + r^\varphi_t)$, where r^φ_t is the interest rate on drawdowns. Because the disbursed credit lines are $p_z \varphi_t$, the profits from credit lines is $p_z \varphi_t \left[\varepsilon \left(1 + r^\varphi_t\right) - 1\right]$.

Disbursed credit lines are a form of loans to firms, and thus, they enter into the capital requirement constraint. Specifically, we assume that

$$n_t \geq \zeta(b_t + p_z \varphi_t), \tag{37}$$

and thus, the bank's equity n_t has to be greater than a fraction ζ of its total lending—term loans plus disbursed credit lines.

We can thus write the banks' problem as

$$\max_{b_t,\, d_t,\, \varphi_t} \; E_t \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ \varepsilon b_t \left(1 - \delta + r_t\right) + p_z \varphi_t \left[\varepsilon \left(1 + r^\varphi_t\right) - 1\right] - R^d_t d_t \right\} dF_{t+1}\left(\varepsilon\right), \tag{38}$$

subject to the budget constraint (10) and the capital requirement constraint (37).

Combining the bank's first-order conditions for b_t and φ_t gives

$$E_t \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ \varepsilon b_t \left(1 - \delta + r_t\right) - R^d_t d_t \right\} dF_{t+1}\left(\varepsilon\right) = \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ p_z \varphi_t \left[\varepsilon \left(1 + r^\varphi_t\right) - 1\right] \right\} dF_{t+1}\left(\varepsilon\right) \tag{39}$$

which in equilibrium pins down a relation between the rate on borrowed capital r_t and the rate on credit lines r^φ_t. Thus, so long as equation (39) holds, banks are indifferent between investing an additional dollar of lending in term loans or credit lines.

The return on equity (12) is replaced by

$$R_{t+1}^{n}=\frac{1}{n_t}\int_{\varepsilon\notin\mathcal{E}_{t+1}}\left\{\varepsilon b_t\left(1-\delta+r_t\right)+p_z\varphi_t\left[\varepsilon\left(1+r_t^{\varphi}\right)-1\right]-R_t^d d_t\right\}dF_{t+1}\left(\varepsilon\right). \tag{40}$$

The thresholds $\underline{\varepsilon}_{t+1}^{FUN}$ and $\underline{\varepsilon}_{t+1}^{RUN}$ that determine the fundamental insolvency region and run regions, (13) and (14), are adjusted to account for the credit lines. For $\underline{\varepsilon}_{t+1}^{FUN}$, we simply account for the fact that the banks' balance sheet now includes the credit lines:

$$\underline{\varepsilon}_{t+1}^{FUN}b_t(1-\delta+r_t)+p_z\varphi_t\left[\underline{\varepsilon}_{t+1}^{FUN}\left(1+r^{\varphi}\right)-1\right]=R_t^d d_t. \tag{41}$$

To pin down the upper threshold of the run region, $\underline{\varepsilon}_{t+1}^{RUN}$, we need to discuss firms' behavior in a run regarding credit lines. We assume that when firms run to withdraw deposits, they also draw down their credit lines if their own productivity shock is z^H (i.e., if the firm needs the credit line to finance its production). We assume that after the drawdown, the balance accrues to the firms' bank account, so that a fraction $1-\phi^f$ of it is uninsured, and this fraction is withdrawn together with the uninsured deposits. Hence, the threshold $\underline{\varepsilon}_{t+1}^{RUN}$ is pinned down by

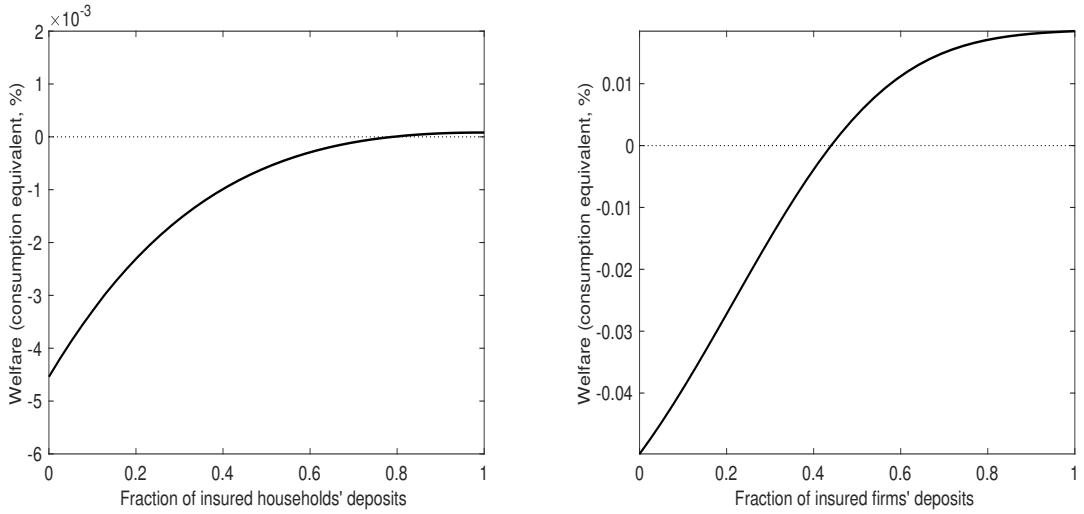
$$\underline{\varepsilon}_{t+1}^{RUN}\left[b_t\left(1-\delta+r_t\right)+p_z\varphi_t\left(1+r^{\varphi}\right)\right]=R_t^d d_t^{ins}+\frac{R_t^d d_t^{uns}}{1-\Upsilon^{tot}}+\phi^f p_z\varphi_t+\frac{\left(1-\phi^f\right)p_z\varphi_t}{1-\Upsilon^{tot}}. \tag{42}$$

Finally, the haircut on deposits is calculated using (26) because, when depositors experience losses, the government does not allow firms to draw down credit lines and, thus equation (26) is unchanged.

F.3 Calibration and simulation

We calibrate the extended model with credit lines using the same approach as in the baseline model. Note that the model includes the same set of parameters. The pre-set parameters are those in Panel A of Table 2, and we use the same values reported there. For the remaining parameters, we use the same targets listed in in Panel B of Table 2 to recalibrate the model.

Relative to the baseline model, the model with credit lines produces similar untargeted moments in regard to business cycle variables. Regarding untargeted banking moments, we note that the model matches almost exactly the ratio of drawn credit line to total credit, where total credit is the sum of term loans (i.e., b_t in the model) and drawn credit lines (i.e., $p_z\varphi_t$ in the model). The model produces a 54% ratio, and the ratio in the data is 53% (Greenwald, Krainer and Paul 2023).



(a) Household Insurance ϕ^h (b) Firm Insurance ϕ^f

Figure 9. Optimal Deposit Insurance in the Model With Credit Lines
The left panel plots household welfare as a function of household deposit insurance ϕ^h, and the right panel plots household welfare as a function of firm deposit insurance ϕ^f, in the model with credit lines. Welfare is expressed in consumption equivalent units.

F.4 Counterfactual analysis

Using the model with credit lines, we repeat the two counterfactual analyses that we analyzed in the main part of the paper. That is, we ask what would have happened if the government had not bailed out the failed banks in 2023, and we compute the optimal level of deposit insurance for firms and households.

When we shock the model with credit lines with both the bank default rate shock (to induce a default rate of 2.3% of the banks, based on the fraction of assets of the banks that failed in 2023) and add also the reduced bailout shock (to $f = 35\%$), we find large negative effects on macroeconomic variables. First, we note that the model with credit lines produces a bigger amplification through bank runs, relative to the baseline model. Because of an increase in bank runs, the default rate on impact is 4.78% in the model with credit lines, versus 3.5% in the baseline model. On impact, GDP drops by 1.61%, labor by 1.38%, and investments by 6.58%. For comparison, in the model in the main part of the paper with $\bar{\theta}$ dropping to zero for firms with losses on uninsured deposits, the same variables drop by 1.18%, 0.83%, and 4.35%, respectively (see Section 5.1.2). Despite the somewhat larger effects, the broader result is unchanged. That is, if firms lose access to their credit lines when they also face losses on uninsured deposits, a crisis with the magnitude of the 2023 bank failures produces a moderately severe recession.

Finally, we turn to the determination of the optimal level of deposit insurance. Our main result about the optimality of insuring 100% of firms' deposits is unchanged. Regarding households' deposits, the welfare function is essentially flat between 90% and 100%, as shown in the right panel Figure 9. Formally, the numerical simulations predict that 100% insurance is optimal for households, but the difference in the consumption equivalent between 90% insurance and 100% insurance is 0 to five decimal places. At this level of approximation (Judd 1998), we find it reasonable to conclude that there is no difference between any level of insurance between 90% and 100%. The same issue does not arise for the welfare function of firms' insurance (Figure 9, right panel), where the optimal level is clearly 100%. Thus, we conclude that the main result about the optimality of higher firms' insurance coverage is robust to using a model with credit lines.

G Extension: Adding Bad Risk-Taking

We now describe the extension in which we add bad risk-taking, that is, we allow banks to invest in projects with low net present value but higher risk, along the logic of Jensen and Meckling (1976). The approach follows Pancost and Robatto (2023).

We extend the problem of banks to allow them to choose the degree of bad risk-taking s_t. A choice of $s_t > 0$ increases the risk of the idiosyncratic shock ε (but leaves the mean unchanged), and involves a cost that reduces the return on bank loans b_t. Specifically, the problem of banks in the extended model is

$$\max_{b_t, d_t, s_t} \int_{\varepsilon \notin \mathcal{E}_{t+1}} \left\{ \varepsilon b_t \left[1 - \delta + r_t - r_t \frac{\lambda_t}{2} (s_t)^2 \right] - R_t^d d_t \right\} dF_{t+1}(\varepsilon; s_t),$$

subject to the same constraint as in the baseline model, that is, the budget and capital requirement constraints in (10) and (11). The cost of risk-shifting is governed by the term $\frac{\lambda_t}{2}(s_t)^2$, where λ_t is an exogenous process specified below.

As in Pancost and Robatto (2023), we assume that ε is distributed according to

$$\varepsilon \sim \begin{cases} 0 & \text{with probability } s_t \\ \frac{\tilde{\varepsilon}}{1 - s_t} & \text{with probability } 1 - s_t \end{cases}$$

where $\tilde{\varepsilon}$ is lognormal with scale parameter σ_t—which follows the same law of motion (29) as in the baseline model—and $\mathbb{E}(\tilde{\varepsilon}) = 1$. This implies, by construction, that $\mathbb{E}(\varepsilon) = 1$ for all s_t.

The first-order condition with respect to s_t is given by

$$\lambda_t s_t r_t \int_{\varepsilon \notin \mathcal{E}} \varepsilon dF^{ln}(\varepsilon) = R_t^d (1-\zeta) \int_{\varepsilon \notin \mathcal{E}} dF_{t+1}^{ln}(\varepsilon), \tag{43}$$

where F_{t+1}^{ln} denotes the lognormal distribution with scale parameter σ_t. On the margin, the cost of risk-shifting depends on the exogenous process λ_t, and in particular, on the reduction in the bank's payoff in the states of the world in which the bank survives. The benefit is the reduction in the expected cost of repaying depositors that are internalized by the bank. Note that changes in deposit insurance do not enter directly in (43), but such changes alter the implicit subsidy paid to banks through deposit insurance and, with it, the return on deposits R_t^d—which affects the benefits of risk shifting.

The evolution of σ_t and λ_t contribute to the time variation in defaults in the model. We assume that these two parameters move together:

$$\frac{\lambda_t}{\bar{\lambda}} = \frac{\sigma_t}{\bar{\sigma}}, \tag{44}$$

where $\bar{\lambda}$ governs the average degree of bad risk taking. Recall that σ_t follows the same law of motion (29) as in the baseline model, and thus, shocks to σ_t will also drive movements in λ_t.

Relative to the baseline model, we have one more parameter that needs to be calibrated, namely, $\bar{\lambda}$. The choice of this parameter affects the degree of bad risk taking in the model. We set $\bar{\lambda}$ to embed a large degree of bad risk taking and produce conservative results. Specifically, we set $\bar{\lambda}$ so that 86.9% of the non-run default is attributable to bad risk taking. This target is based on the importance of bad risk taking in Pancost and Robatto (2023), but more generally, it likely represents an upper bound on the default rate driven by banks' risk-shifting.

H Extension: Banking with Negative Equity

In this section, we enrich the bank's problem by allowing banks with negative equity to operate for some time, rather than being immediately shut down. Similar to the baseline model, a bank created at time t collects deposits and makes loans in that period, and then it receives a shock ε at $t+1$ that affects the cash flow from loan repayments. If the shock is large enough and the bank is solvent at $t+1$, it returns its resources after repaying depositors to shareholders (i.e., households), provided that it is not subject to a run: this is the same as in the baseline model. But if the

bank has negative equity at $t+1$, and provided it is not subject to a run, we allow it to operate for another period, that is, take deposits and issue loans at $t+1$. Operating with negative equity at $t+1$ is valuable for shareholders because the bank can "gamble for resurrection": the bank receives another shock ε at $t+2$ that can make the bank solvent again. At that point, we assume for simplicity that the bank is always shut down by the regulator: if it is insolvent, its uninsured depositors are either bailed out or experience losses, and if it is solvent, the uninsured depositors are fully repaid and any additional resource is used to repay shareholders.

The extension is motivated by both the 2023 banking crisis and the Savings & Loans crisis, and the fact that the regulation used in practice does not force banks to mark-to-market their equity every period. Specifically, banks can use historical cost accounting to value some of their securities (Kim, Kim and Ryan, 2019), they can evaluate loans at book value rather than discounting their cash flow in case the interest rates changes (Jiang et al., 2023), and delayed loss accounting rules might keep banks' regulatory capital artificially high (Begenau et al., 2021).

At time t, households invest $n_t^{pos} > 0$ in the banking sector, creating a unit mass of positive-equity banks. These banks issue deposits d_t^{pos} and invest in assets b_t^{pos}, subject to the same capital requirement and budget constraint as the baseline model:

$$\begin{aligned} n_t^{pos} &\geq \zeta b_t^{pos} \\ b_t^{pos} &= d_t^{pos} + n_t^{pos}. \end{aligned}$$

Likewise, the thresholds for fundamental and run defaults, which only affect positive-equity banks, are similar to the baseline model:

$$\begin{aligned} \underline{\varepsilon}_{t+1}^{FUN} b_t^{pos}(1-\delta+r_t) &= R_t^d d_t^{pos} \\ \underline{\varepsilon}_{t+1}^{RUN}\ b_t^{pos}\,(1-\delta+r_t) &= R_t^d \iota_t d_t^{pos} + \frac{R_t^d d_t^{pos}\,(1-\iota_t)}{1-\Upsilon^{tot}}, \end{aligned}$$

where $\iota_t \equiv d_t^{ins}/d_t$ is the fraction of insured deposits across all types of banks. We assume that positive and negative equity banks attract the same depositors and thus have the same fraction of uninsured deposits.

For a positive-equity bank, there are three possibilities at $t+1$, depending on the realization of its shock ε at $t+1$.

(i) If $\varepsilon > \underline{\varepsilon}_{t+1}^{RUN}$, the bank is outside the run region, and it pays a dividend for sure, as in the

baseline model.

(ii) If $\underline{\varepsilon}_{t+1}^{FUN} < \varepsilon < \underline{\varepsilon}_{t+1}^{RUN}$, the bank is in the run region. If the bank is subject to a run, it is taken over by the regulator and liquidated immediately. If is not subject to a run, it pays a dividend. These outcomes are again the same as in the baseline model.

(iii) If $\varepsilon < \underline{\varepsilon}_{t+1}^{FUN}$, the bank's liabilities exceed the assets. If the bank is subject to a run, it is taken over by the regulator and liquidated immediately.[30] But if it is not subject to a run, it operates again at $t+1$ (i.e., it takes deposits and issues loans) as a negative-equity bank.

At the beginning of $t+1$, the measure of banks of type (iii) not subject to runs (i.e., negative-equity banks) is given by

$$m_{t+1} = [1 - \pi (1 - f)] \int_0^{\underline{\varepsilon}_{t+1}^{FUN}} dF_{t+1} (\varepsilon) .$$

The total net worth of negative-equity banks at time $t+1$ is n_{t+1}^{neg}, given by

$$n_{t+1}^{neg} = [1 - \pi (1 - f)] \int_0^{\underline{\varepsilon}_{t+1}^{FUN}} \left[\varepsilon b_t^{pos} (1 - \delta + r_t) - R_t^d d_t^{pos} \right] dF_{t+1} (\varepsilon) < 0,$$

where $n_{t+1}^{neg} < 0$ follows from the definition of $\underline{\varepsilon}_{t+1}^{FUN}$.

We assume that negative-equity banks operate together as a single representative bank.[31] We denote the total assets and total deposits at $t+1$ of the mass m_{t+1} of negative-equity banks as b_{t+1}^{neg} and d_{t+1}^{neg}, respectively. Negative equity banks cannot be subject to the same capital requirement as positive-equity banks—if they did, they could not have any assets, because their equity is negative. Thus, we assume that they invest in the same assets as the previous period, so that the total stock of assets at negative equity banks is $b_{t+1}^{neg} = m_{t+1} b_t^{pos}$.[32] Deposits at negative-equity banks are then set by the budget constraint $d_{t+1}^{neg} = b_{t+1}^{neg} - n_{t+1}^{neg}$. Thus, negative-equity banks finance their losses for one period by issuing more deposits.

At $t+2$, negative equity banks pay a dividend and exit (if they are solvent at $t+2$) or are

[30] Differently from the baseline model, the run region includes banks with $\varepsilon < \underline{\varepsilon}_{t+1}^{FUN}$ because banks with negative equity are not immediately shut down by the regulator.

[31] This implies that there is no heterogeneity in the leverage of negative-equity banks, and allows us to compute one single cutoff for ε to determine if the bank is solvent at $t+2$.

[32] This is equivalent to assuming that the capital requirement of these banks depend on the lagged value of their capital, consistent with the motivation discussed earlier about regulation that allows banks to use historical cost accounting and other accounting rules based on book values. For more discussion on the link between capital requirements and regulations that allow banks to evaluate their assets at book value and historical costs, see Orame, Ramcharan and Robatto (2023).

resolved by the government, depending on the value of ε they receive at $t+2$. In particular, negative-equity banks at $t+1$ that receive a value of $\varepsilon_{t+2} > \underline{\varepsilon}_{t+2}^{NEG}$ pay out a dividend div_{t+2}^{neg}, and the remainder are resolved by the government, where $\underline{\varepsilon}_{t+2}^{NEG}$ is defined by

$$\underline{\varepsilon}_{t+2}^{NEG} b_{t+1}^{neg} \left(1-\delta+r_{t+1}\right) = R_{t+1}^{d} d_{t+1}^{neg}.$$

Thus, the investment of n_t^{pos} at the beginning of time t results in dividends from three types of banks in both $t+1$ and $t+2$. Dividends from positive-equity banks at $t+1$, including banks both inside and outside the run region, are given by

$$\begin{aligned} div_{t+1}^{pos} &= \left[1-\pi\left(1-f\right)\right] \int_{\underline{\varepsilon}_{t+1}^{FUN}}^{\underline{\varepsilon}_{t+1}^{RUN}} \left[\varepsilon b_t^{pos}\left(1-\delta+r_t\right) - R_t^d d_t^{pos}\right] dF_{t+1}\left(\varepsilon\right) \\ &\quad + \int_{\underline{\varepsilon}_{t+1}^{RUN}}^{\infty} \left[\varepsilon b_t^{pos}\left(1-\delta+r_t\right) - R_t^d d_t^{pos}\right] dF_{t+1}\left(\varepsilon\right), \end{aligned}$$

and dividends from negative-equity banks at $t+2$ are given by

$$div_{t+2}^{neg} = \int_{\underline{\varepsilon}_{t+2}^{NEG}}^{\infty} \left[\varepsilon b_{t+1}^{neg}\left(1-\delta+r_{t+1}\right) - R_{t+1}^d d_{t+1}^{neg}\right] dF_{t+2}\left(\varepsilon\right).$$

We can thus write the first-order condition that pins down the households' choice of n_t^{pos}:

$$1 = \beta\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\left[\frac{div_{t+1}^{pos}}{n_t^{pos}} + \beta\frac{\Lambda_{t+2}}{\Lambda_{t+1}}\frac{div_{t+2}^{neg}}{n_t^{pos}}\right]\right\}.$$

The total bank default rate at time $t+1$ includes positive-equity banks who began at time t and experience a run, as well as negative-equity banks who began at time $t-1$ and received a low value of ε_{t+1}:

$$p_{t+1}^{default} = \frac{m_t \int_0^{\underline{\varepsilon}_{t+1}^{NEG}} dF_{t+1}\left(\varepsilon\right) + \pi\left(1-f\right)\int_0^{\underline{\varepsilon}_{t+1}^{RUN}} dF_{t+1}\left(\varepsilon\right)}{1+m_t}.$$

Notice that this default probability uses m_t and $\underline{\varepsilon}_{t+1}^{NEG}$, since at time $t+1$ the government closes negative-equity banks that were begun at time $t-1$. The haircut on deposits at failed banks at $t+1$ is then pinned down by

$$\left(1-\nu_{t+1}\right) R_t^d d_{t+1}^{default} = \left(1-\Upsilon^{tot}\right)\left(1-\delta+r_t\right) b_{t+1}^{default}$$

where $d_{t+1}^{default}$ and $b_{t+1}^{default}$ are the liabilities and assets of the banks that fail:

$$d_{t+1}^{default} = \int_0^{\underline{\varepsilon}_{t+1}^{NEG}} d_t^{neg} dF_{t+1}(\varepsilon) + \pi(1-f) \int_0^{\underline{\varepsilon}_{t+1}^{RUN}} d_t^{pos} dF_{t+1}(\varepsilon)$$

and

$$b_{t+1}^{default} = \int_0^{\underline{\varepsilon}_{t+1}^{NEG}} \varepsilon b_t^{neg} dF_{t+1}(\varepsilon) + \pi(1-f) \int_0^{\underline{\varepsilon}_{t+1}^{RUN}} \varepsilon b_t^{pos} dF_{t+1}(\varepsilon).$$

We recalibrate the model to match the moments listed in Panel B of Table 2, and then run our counterfactuals. Relative to the model in the main part of the paper, there is just a small difference in the way we compute the effects of the reduced bailout probability f. As in the baseline model, we set the shock to σ_t to induce a default of 2.3% of banks, but because it takes one period for insolvent banks to exit, the shock to σ_t produces the 2.3% default rate at $t+1$. Thus, when we add the reduced bailout probability f, we do so one period after the shock to σ_t. Similarly, the effects on GDP reported in Table 4 refers to the effects that arise at $t+1$, that is, one period after the shock to σ_t and in the same period in which we reduce the bailout probability f.