Assessing Options for Deposit Insurance Reform: An Infinite-Horizon Approach*

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Abstract

In March 2023, unusually fast depositor withdrawals led to the failure of several US banks. In response, the government provided an implicit temporary increase in deposit insurance by covering 100 % of the ex-ante uninsured depositors. These events have reignited a debate on deposit insurance reform. This paper contributes to this discussion by developing a dynamic general equilibrium model that incorporates: (a) idiosyncratic bank failures, (b) contagion from failing banks to solvent banks and the broader economy, and (c) state-contingent deposit insurance. I calibrate the model to US data and use it to assess several options for deposit insurance reform. First, I show that, under fast government response, state-contingent deposit insurance is the optimal policy. Second, if the government's response is delayed, fixed deposit insurance is preferred to the state-contingent policy. Third, delayed government response does not justify full deposit insurance at all times: the optimal fixed deposit insurance policy covers around 65 % of total deposits.

JEL classification: D31, E21, G01, G21.

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1. Introduction

This paper studies the optimal design of deposit insurance through a dynamic general equilibrium model that incorporates crucial features of the recent US banking turmoil. In March 2023, depositor withdrawals forced three mid-size US banks into early liquidation. Shortly after, the US government triggered the Systemic Risk Exception (SRE) to cover 100% of the ex-ante uninsured depositors of these failed banks. Treasury Secretary Janet Yellen claimed that "similar actions could be warranted if smaller institutions suffer deposit runs that pose the risk of contagion", signaling an implicit increase in deposit insurance coverage.[1] Figure 1 provides evidence suggesting that the recent turmoil was similar to other US banking crises: it was marked by large-scale panics, failure of a fraction of the banking sector, and some form ex-post increase in deposit insurance coverage.

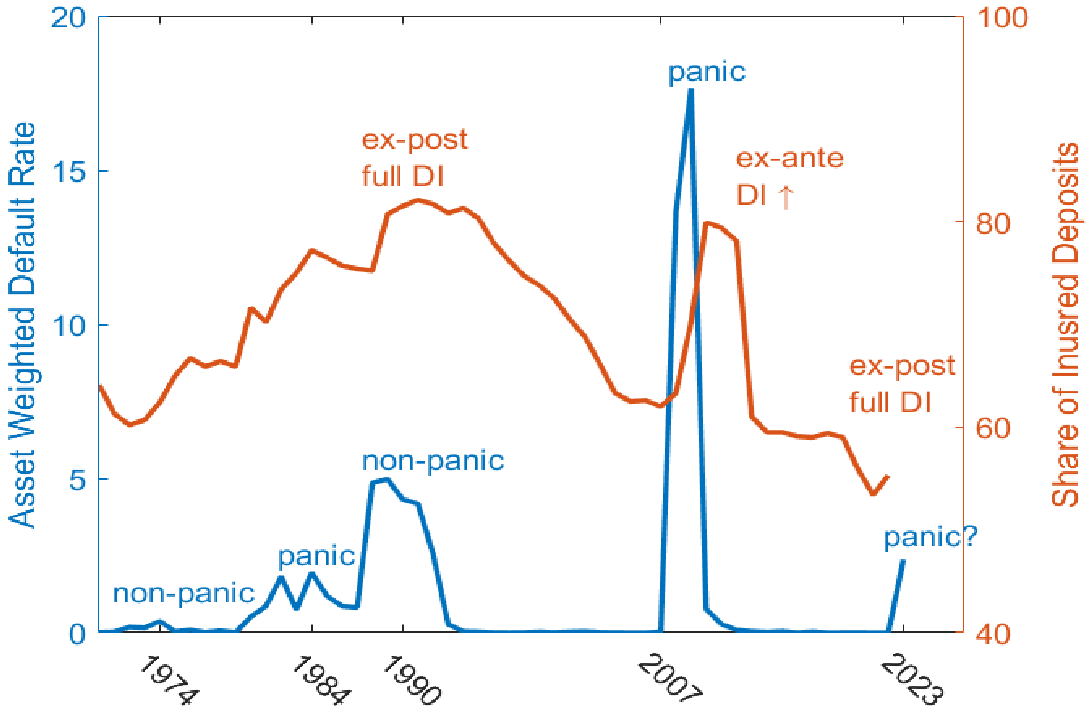
Amid these developments, the FDIC proposed a series of alternatives for deposit insurance reform (FDIC, 2023). The first proposal consists of increasing the deposit insurance limits beyond current levels, but to a level below full insurance. Their argument is that the current level may be insufficient to prevent panic-driven crises, while large increases in coverage could generate too much moral hazard. The second proposal suggests implementing full deposit insurance at all times. The rationale for this proposal is that ex-post government interventions might occur too late to limit contagion. Arguably, this concern is rooted on two observations. On one hand, ex-post increases in deposit insurance coverage are potentially slow to implement.[2] On the other, recent evidence indicates that bank-runs might materialize much faster than previously thought (see Rose, 2023; FDIC, 2023).

What is missing from this debate is a comprehensive framework to assess the desirability

[1]Janet Yellen clarified that these actions were aimed at containing systemic risk, rather than to bail out a specific depositors or sectors (see Lawder, 2023).

[2]This delay may result from legal constraints. For instance, invoking the S.R.E. requires joint approval by the Treasury, Federal Reserve and the FDIC. In 2008, the temporary increase in coverage was approved by U.S. Congress, but became legally effective over one month after it was formally approved.

Figure 1: US Banking Crises and Deposit Insurance



Notes: This figure shows the asset weighted default rate of US commercial banks (blue line, left axis) and the evolution of deposit insurance (red line, right axis). This data is collected from the FDIC. The classification of US banking crises is based on Baron et al. (2021), with the exception of the 2023 crises. I manually collected that for the labels indicating ex-ante and ex-post changes in DI coverage based on reports and articles.

of these proposals. To address this gap, I develop a model featuring: (1) idiosyncratic, liquidity-driven bank failures; (2) dynamic contagion effects from failing banks to the real economy; and (3) state-contingent deposit insurance. These model elements are absent from standard two-period partial equilibrium models of systemic bank failure, such as those in the tradition of Diamond and Dybvig (1983), but they enable a more nuanced analysis of key aspects of deposit insurance reform debate.

I calibrate the model to the US economy, and use it as a framework to examine the relationship between deposit insurance, banking crises, and real economic activity. The primary insight from my analysis is that the current US approach of increasing deposit insurance in times of distress is a double-edged sword. If the government can observe the state of the economy in real time, and change the deposit insurance coverage contemporaneously, state-contingent deposit insurance can prevent liquidity driven banking crises while inducing relatively small moral hazard costs. However, in a more realistic scenario where government's response is delayed, the effectiveness of state-contingent deposit insurance diminishes significantly. I demonstrate that, under implementation delays, a fixed ex-ante deposit insurance policy is more desirable than a state-contingent policy. Specifically, the optimal deposit insurance policy covers 65 % of deposits at all times - approximately 10 percentage points higher than the coverage level in 2023, but still well below full insurance.

To fix ideas, Section 2. presents a one-period partial equilibrium framework with fractional bank default.[3] The model features a continuum of intermediaries investing in illiquid assets and facing idiosyncratic shocks. Fundamental defaults occur when banks' asset returns fall below the value of banks' liabilities. Liquidity failures arise when depositors fear that fire-sale liquidation of bank assets would be insufficient to cover early withdrawals. Following Goldstein and Pauzner (2005) and De Groot (2021), liquidity failures emerge as a unique equilibrium from a coordination game across depositors. The government guarantees a fraction of household deposits. I show that the rationale for the effectiveness of deposit insurance holds despite the presence of idiosyncratic bank defaults and partial insurance. In particular, I find that increases in partial deposit insurance coverage are welfare improving only if they prevent liquidity-driven failures of fundamentally solvent banks; otherwise, they are welfare neutral. Therefore, full deposit insurance is weakly optimal.

In Section 3. I incorporate this framework into an otherwise standard dynamic general equilibrium banking model (see e.g. Bernanke et al., 1999; Gertler and Karadi, 2011; Elenev et al., 2021). Similar to other models in the literature, deteriorating bank assets constrain the intermediation capacity of the banking sector and feed back into total capital accumulation

[3] This section builds on the approach of Diamond and Dybvig (1983), Cooper and Ross (2002), Allen et al. (2018), and Dávila and Goldstein (2023).

and real economic activity. In my model, increases in bank asset risk induce sharp increases in fundamental defaults (Mendicino et al., 2020), whereas deterioration in bank asset liquidity prompts households to withdraw their deposits, leading to bank-runs (De Groot, 2021). Banks internalize how these risks affect their future expected profits through their cost of debt, and adjust their risk profile accordingly. Crucially, higher deposit insurance reduces the sensitivity of deposit rates to default risk, and leads banks to take on excessive risks. Therefore, this model element introduces social costs of high deposit insurance.

Since deposit insurance reduces liquidity default risk but increases fundamental default risk, the costs and benefits of deposit insurance crucially depend on the likelihood and severity of liquidity and fundamental banking crises. To quantify this trade-off accurately, in Section 4.1 I calibrate the model to match the probability, persistence and severity of each crises type using the classification from Baron et al. (2021). In Section 4.2, I simulate the dynamics of banking crises based on the calibrated model. A key feature of the model is that, even though the increases in bank defaults are relatively short-lived, they lead to a highly persistent drop in the size of the banking sector, which subsequently feeds back into real economic activity. Thus, the model captures the concept of dynamic contagion central to the current debate on deposit insurance reform.

In Section 5., I assess the aforementioned FDIC proposals using the calibrated model. In Section 5.1, I show that increasing ex-ante deposit insurance coverage effectively prevents liquidity crises. However, it also induces banks to take on more risk, which results in more severe fundamentally-driven crises. The optimal level of fixed ex-ante deposit insurance covers 65 % of total deposits. This policy completely eliminates liquidity-driven crises while incurring relatively modest moral hazard costs. This coverage level is about 10 percentage points larger than the insured deposits share as of 2023.

Section 5.2 evaluates whether the US approach of keeping a relatively low coverage in good times, and increasing it in bad times is desirable. I begin with the scenario where the government can implement the state-contingent deposit insurance policy without delays. In particular, I allow the government to: (1) observe the aggregate state of the economy, and (2) adjust coverage levels before households make their withdrawal decisions. Unsurprisingly, state-contingent deposit insurance is as effective as the ex-ante policy at preventing liquidity crises. However, because it limits coverage increases to specific circumstances, this policy reduces the increase in ex-ante bank risk-taking and mitigates the increase in fundamentally driven defaults relative fixed ex-ante coverage increases. Therefore, assuming no implementation frictions, my work rationalizes ex-post increases in deposit insurance that are typically carried out by the U.S. government.

This assumption is arguably unrealistic. Section 5.3 relaxes it by assuming that the increase in deposit insurance take effect one quarter after the economy has transitioned from the good to the bad aggregate state.[4] Consequently, there are some periods in which bank asset liquidity deteriorates, but deposit insurance cannot prevent households from withdrawing, resulting in liquidity-driven failures. I show that, this implementation delay erases the benefits of state-contingent deposit insurance relative to fixed deposit insurance. This result arises from two counter-acting forces. On one hand, ex-post increases are unable to prevent the initial impact of liquidity crises and also induce moral hazard. On the other, since liquidity crises are persistent, the government can effectively contain further bank defaults and therefore mitigates the effects of the crises. It turns out that mitigation gains are small relative to the costs of the initial impact of the crises and the moral hazard costs. As a result, increases in fixed ex-ante coverage are more desirable than increases in state-contingent deposit insurance.

Relate Literature. My work relates to two strands of literature. First, it relates to a large body of work on two-period bank-run models of systemic bank failures. Some papers focus on deposit insurance design (see e.g. Diamond and Dybvig, 1983; Cooper and Kempf, 2016; Allen et al., 2018; Dávila and Goldstein, 2023), while others examine the

[4]To be clear, the model is silent about whether this implementation lag arises from legal constraints, informational constraints or depositor withdrawals being too fast.

efficiency properties of bank-runs (Allen and Gale, 1998), the role of bail-outs (Keister, 2016) or financial regulation more broadly (Kashyap et al., 2020). In line with Goldstein and Pauzner (2005) and Allen et al. (2018), bank-runs in my model materialize as a unique equilibrium outcome from a global game across depositors, rather than through sunspots. Overall, my contribution to this literature if to study deposit insurance in a dynamic general equilibrium of fractional bank default.

Second, my work relates to a series of papers that develop dynamic models of bank default. Gertler et al. (2020) Faria-e Castro (2021), and Rottner (2023) study system-wide panics arising as a sunspot equilibrium, building on the seminal work of Gertler and Kiyotaki (2015). Other research features fractional defaults due to either fundamental reasons (Begenau and Landvoigt, 2018; Mendicino et al., 2020; Elenev et al., 2021) or depositor withdrawals (Bianchi, 2016; Amador and Bianchi, 2021; De Groot, 2021). My contribution lies on focusing specifically on the design of deposit insurance.

2. Partial Equilibrium

2.1 Environment

I consider a one-period economy, populated by a continuum of households h, a continuum of banks b, and a deposit insurance agency (DIA). Each bank operates under limited liability and faces idiosyncratic returns ω_b, drawn from a cumulative distribution $F(\omega)$. Banks invest in capital K_b, financed through their own equity and by issuing demand deposits D_b. Capital yields an aggregate return R_k, while deposits offer a promised interest rate R_d, conditional on rolling over. The realized return on deposits depends on banks' default choices, households roll-over decisions, and deposit insurance policy.

If an individual bank b does not default, a household h that chooses to roll-over its deposits receives a return $R_d < R_k$. A household choosing to withdraw receives a lower return $\epsilon < R_d$. To pay early-withdrawing households, the bank can fire-sale capital at price $\lambda < 1$. Bank b defaults if it lacks sufficient resources to pay back the withdrawing or rolling-over households.

The DIA takes over assets of each defaulting bank b and liquidates them at fire-sale price λ. It guarantees at least a fraction κ of their deposits. If the per-depositor recovery rate, RV_b, exceeds the insurance limit κ, the DIA pays each household RV_b instead. To maintain a balanced budget, the DIA covers any deficits by levying lump-sum taxes T on households.

Each household h's decision to roll-over its deposits with bank b is strategic: they depend on its beliefs about the actions of the bank b, the DIA and the other households. These beliefs are based on a noisy signal $\hat{\omega}_{h,b} = \omega_b + \nu_h$, where the noise term ν is uniformly distributed as $\nu \sim U(-\bar{\nu}, \bar{\nu})$.

Table 1: Timing of actions

Morning	**Afternoon**
Returns ω_b and signals are realized $\hat{\omega}_{h,b}$	Surviving b pay households or default
Each h chooses to withdraw or roll-over	DIA levies taxes and makes payments
If b cannot pay withdrawals it defaults	Performing banks pays profits and deposits

Each period, is split in two sub-periods: morning and afternoon. The sequence of actions is outlined in Table 1. Two timing assumptions are worth discussing. First, I assume that a bank anticipating an afternoon default will not default in the morning. This assumption is essential to derive a unique panic default threshold and allows for a crucial distinction between two types of failures: morning failures are *liquidity*-driven whereas afternoon failures are *fundamentally*-driven. Second, I assume households have no morning consumption needs. Although this assumption deviates from the framework of Diamond and Dybvig (1983), it ensures households are ex-post identical, a feature that will prove useful when I introduce the dynamic model in Section 3..

2.2 Individual banks

Each b is ex-ante identical, and begins the period with K_b capital and D_b deposits. In the morning, the idiosyncratic return shock ω_b is realized, and a proportion p of households withdraws. The morning payments due to these withdrawing households are $p\epsilon D_b$, which the bank must cover by liquidating assets at fire-sale price λ. Given realized return ω_b, the morning default threshold p_m corresponds to the value $p \in [0, 1]$ at which the payments of early withdrawals equal the liquidation value of bank assets. Therefore, p_m solves $\lambda\omega_b R_k K_b = p_m \epsilon R_d D_b$, which can be re-arranged as

$$p_m(\omega_b) = \frac{\lambda\omega_b}{\epsilon\bar{\omega}}, \tag{1}$$

where $\bar{\omega} = \frac{R_d(1-\phi)}{R_k}$ is the fundamental default threshold, and ϕ denotes the binding capital requirement.[5] If $p < p_m(\omega_b)$, the bank b sells capital to meet withdrawal demands and moves to the afternoon. The amount of capital required to meet these payments $\tilde{K}_b$, satisfies $\lambda\omega_b R_k \tilde{K}_b = p\epsilon R_d D_b$.

A bank that survives the morning moves into the afternoon with capital $\bar{K}_b$, given by

$$\bar{K}_b = K_b - \frac{p\epsilon R_d D_b}{\lambda\omega_b R_k}. \tag{2}$$

In the afternoon, the bank must pay back the remaining depositors $(1-p)R_d D_b$, using its output $\omega_b R_k \bar{K}_b$. The afternoon default threshold p_a is the level of $p \in (p_m, 1]$ at which the bank's output equals the payments owed to rolling-over depositors, satisfying

$$\omega_b R_k \bar{K}_b = (1 - p_a) R_d D_b. \tag{3}$$

Re-arranging this expression, and substituting in (1) and (2), the afternoon threshold p_a can

[5] In Section 3. I show that bank optimal choices are such that the capital requirement binds in equilibrium.

be expressed as a function of p_m:

$$p_a(\omega_b) = \frac{p_m(\omega_b)\epsilon - \lambda}{\epsilon - \lambda} \tag{4}$$

2.3 Deposit Insurance Agency

Having characterized the actions of individual banks b, I can now detail the behavior of the DIA. For each defaulting, the the DIA guarantees a minimum payment equal to the deposit insurance limit κ. However, it may pay more if the recovery value per depositor exceeds this limit. To meet these payment obligations, the DIA can liquidate bank assets within the period, subject to the same fire-sale constraints as the private sector.[6]

Consider first the case where $p \geq p_m(\omega_b)$, associated with the case where the bank defaults in the morning. Since banks make morning payments until they exhaust their resources, when a bank defaults in the morning, the DIA recovers no assets and must pay the remaining depositors the insurance limit κR_d.

Now, suppose that $p_a(\omega_b) \geq p$, corresponding with the case where bank b defaults in the afternoon. In this case, the DIA recovers $\bar{K}_b$. The total liabilities of the bank amount to $R_d D_b(1-p)$, which must be covered by selling bank assets at fire-sale price λ. The recovery value per depositor RV_b is given by

$$RV_b = \frac{\lambda \omega_b R_k \bar{K}_b}{(1-p)D_b}. \tag{5}$$

Substituting equations (1)-(4) into (5), we can express RV_b as a function of the morning default threshold:

$$RV_b = \frac{1}{1-p} \cdot [\, p_m(\omega_b) - p\,]. \tag{6}$$

It follows that RV_b is decreasing in p, for any $p \in [p_a, p_m)$. Thus, for any bank that defaults

[6] In practice the FDIC disburses payments above the deposit insurance limit sequentially as it gradually liquidates the bank's assets. Thus, the implicit assumption here pertains to the timing of DIA payments.

in the afternoon, the resources available to the DIA are decreasing in the proportion of early-withdrawing households. This feature generates a strategic complementarity among depositors, which I will discuss shortly.

Since the DIA can pay above the limit κ, the payments made by the DIA to each depositor of a bank that defaults in the afternoon are given by $Max\{RV_b, \kappa R_d\}$. Given that RV_b is decreasing in p, there is point in the range $p \in (p_m, p_a)$, denoted $p_\kappa(\omega_b)$, where $RV_b = \kappa R_d$. At this point, the recovery value of the bank is exactly the same as the deposit insurance limit. Imposing this condition and re-arranging yields the following expression for $p_\kappa(\omega_b)$

$$p_\kappa(\omega_b) = \frac{p_m(\omega_b) - \kappa R_d}{1 - \kappa R_d}. \tag{7}$$

Below $p_\kappa(\omega_b)$ each late-withdrawing depositor receives more than the limit κ and the DIA breaks even. Above this threshold, the DIA pays the limit κ and incurs a deficit, which is financed by lump-sum taxes.

2.4 Households

Having characterized the default decisions of banks as a function of p_b and ω_b, as well as the payments made by the DIA for defaulting banks, I am in a position to solve for the roll-over decision of households for each bank b. This decision, in turn, determines the share of households that withdraw for each bank.

In the morning, each household h receives a noisy signal $\hat{\omega}_{h,b}$ regarding the idiosyncratic return of the bank ω_b. Given this signal and their beliefs about other agents actions, $\hat{p}_{-h}(\hat{\omega}_{h,b})$, household h's subjective pay-offs from rolling over (denoted as R) and withdrawing (denoted as W) are summarized by Table 2. I make three assumptions throughout this analysis: (a) $\epsilon = \frac{1}{R_d}$, which implies that absent default, early-withdrawals imply forgoing interest rate payments; (b) $\kappa < \epsilon$, ensuring that for some values of ω_b, it is always optimal to withdraw; and (c) in the event of a morning default, whether a household receives payments from the bank depends on a random position in a queue. I will now characterize households' optimal decisions as a function of their beliefs about others' actions.

Table 2: Pay-offs of R and W

Roll-over (R)	Withdraw (W)	$\hat{p}_{-h}(\hat{\omega}_{h,b})$	Bank b decision
R_d	1	$(0, \hat{p}_a(\hat{\omega}_{h,b})]$	Survive morning and afternoon
RV_b	1	$(\hat{p}_a(\hat{\omega}_{h,b}), \hat{p}_\kappa(\hat{\omega}_{h,b}))$	Afternoon default and $RV_b \geq \kappa R_d$
κR_d	1	$(\hat{p}_k(\hat{\omega}_{h,b}), \hat{p}_m(\hat{\omega}_{h,b})]$	Afternoon default and $RV_b < \kappa R_d$
κR_d	$[\frac{1-\hat{p}}{\hat{p}}\kappa + \frac{1}{\hat{p}}\epsilon]R_d$	$(\hat{p}_m(\hat{\omega}_{h,b}), 1]$	Morning default

First, consider a scenario where household h believes the bank will survive both morning and afternoon, corresponding to the first row of Table 2 with beliefs $p_{-h}(\hat{\omega}_{h,b}) < p_a(\hat{\omega}_{h,b})$. In this case, choosing R yields pay-off R_d, while choosing W yields a pay-off of 1. Thus, household h chooses to roll over (R).

Second, consider the scenario where household h believes the bank will default in the morning, which corresponds to the condition that $p_m(\hat{\omega}_{h,b}) \leq p_{-h}(\hat{\omega}_{h,b})$, with pay-offs described in the fourth row of Table 2. If household h chooses R, it receives κR^d with certainty. In contrast, if h chooses W it gets ϵR_d if it arrives "early" in the queue, and κR_d if it arrives "late" in the queue. The perceived probability of arriving "early" is given by $\frac{1}{p_{-h}(\hat{\omega}_{h,b})}$, and that of arriving "late" is given by $\frac{1-p_{-h}(\hat{\omega}_{h,b})}{p_{-h}(\hat{\omega}_{h,b})}$. Therefore, it is optimal for h to withdraw.

The third row describes the case where the bank defaults in the afternoon, but the DIA recovers less than the limit. This occurs when $p_k(\hat{\omega}_{h,b}) \leq p_{-h}(\hat{\omega}_{h,b}) < p_m(\hat{\omega}_{h,b})$. In this situation h gets κR^d from R, and ϵR^d from W. Under assumption (b) it follows that it is optimal for the household to withdraw early.

The key to this global game arises in the scenario where the bank defaults in the afternoon but the DIA recovers more than the deposit insurance limit. This corresponds to the case where $p_a(\hat{\omega}_{h,b}) \leq p_{-h}(\hat{\omega}_{h,b}) < p_k(\hat{\omega}_{h,b})$, with pay-offs outlined in the second row of Table 2. In this case, the optimal choice of h crucially depends on $p_{-h}(\hat{\omega}_{h,b})$, which becomes evident once we consider sub-cases. At $p_a(\hat{\omega}_{h,b}) \leq p_{-h}(\hat{\omega}_{h,b})$, the pay-offs are equivalent to those of the first row, so it is optimal for h to choose R. At $p(\hat{\omega}_{h,b}) = p_k(\hat{\omega}_{h,b})$ the pay-offs are equivalent to those of row three so it is optimal to choose W.

What happens for values between $p_a(\hat{\omega}_{h,b})$ and $p_k(\hat{\omega}_{h,b})$? Since the pay-offs from W are decreasing and continuous in $p_{-h}(\hat{\omega}_{h,b})$, while those of R are constant, it follows that there must be a point in the space of $p_{-h}(\hat{\omega}_{h,b})$ such that h is indifferent between R and W. This implies that the incentives to withdraw are strictly increasing in the share or households choosing the same action. The game, therefore, features a strategic complementarity and crosses the indifference line only once in within this region.

Given the payoff structure of the game described above, I derive the first result of the paper which I present in Proposition 1 below. This proposition states that under the previously outlined assumptions, and if the noise of the signal is arbitrarily small but larger than 0, there exists a unique liquidity default threshold ω^*. For any realization $\omega_b < \omega^*$ all households withdraw early and the bank fails in the morning. For any realization $\omega_b \geq \omega^*$ no household withdraws and the bank survives the morning.

Proposition 1. *Existence and Uniquness of Panic Threshold*
$\exists! \omega^* \in [0, \infty)$ *such that* $p = 1$ *if* $\hat{\omega} < \hat{\omega}^*$, *and* $p = 0$ *if* $\hat{\omega} \geq \hat{\omega}^*$ *as long as:*

- $\kappa < \epsilon$ *and* $\bar{\nu} \to 0$.
- *there exists a unique* ω^* *such that* $p_m(\omega^*)\Omega_1 + \Omega_2 + Ln(p_m(\omega^*))(1 + \kappa R_d) = 0$

where $\Omega_1 = \epsilon \frac{R_d - 1}{\epsilon - \lambda} - \frac{\kappa R_d}{1 - \kappa R_d} + \kappa R_d + Ln(\frac{\lambda - \epsilon}{1 - \kappa R_d})$ *and* $\Omega_2 = -\frac{\lambda(R_d - 1)}{1 - \lambda} + \frac{(\kappa R_d)^2}{1 - \kappa R_d}) - Ln(1 - \kappa R_d)$.

The full proof is relegated to Appendix A.2 and closely follows Goldstein and Pauzner (2005), De Groot (2021), and Allen et al. (2018). I proceed in two steps.

In the first step I find an idiosyncratic return realization, denoted ω^*, such that agents are indifferent between withdrawing and rolling over. Since agents know the bounds of the noise term, and their signal $\hat{\omega}_{h,b}$, they can bound the set of signals other agents receive. This allows them to form beliefs about other agents' signals, given their own signal. Imposing $\bar{\nu} \to 0$, agents know the expected actions of other agents. In particular, they know that for any $\omega_{-h,b} < \omega^*$ other agents withdraw, and for any $\omega_{-h,b} > \omega^*$ all agents roll-over. I then find ω^* by taking expectations over pay-offs and setting them to zero.

The second step consists of showing that ω^* is indeed a unique equilibrium. This follows from a series of conditions on household's pay-off outlined by De Groot (2021). The key conditions are single-crossing, monotonicity and uniform limit dominance. Single-crossing requires that the pay-off function crosses zero only once, which I already discussed. Monotonicity requires that the pay-off function is weakly increasing in the signal for all the values of p, which follows from the assumptions that the DIA can pay more than the limit, and the random queue assumption. Uniform limit dominance requires that there exist value of the signals such that each action (withdrawing and rolling-over) is optimal regardless of others' actions. This condition holds due to the assumption that $\omega \in [0, \infty)$. [7]

2.5 Resource Constraint

The effective default threshold $\tilde{\omega}$ is given by the maximum between the fundamental and liquidity default thresholds:

$$\tilde{\omega} = Max\{\bar{\omega}, \omega^*\}. \tag{8}$$

Therefore, the total share of defaulting banks is given by the mass of banks with return realizations below $\tilde{\omega}$

$$F(\tilde{\omega}) = \int_0^{\tilde{\omega}} dF(\tilde{\omega}), \tag{9}$$

[7] When ω is so high that the bank will never default, it is optimal to roll-over for any $p \in [0, 1]$. When ω is close to 0, the bank defaults in the afternoon, the DIA recovers less than the limit, and since $\epsilon > \kappa$ it is always optimal to withdraw. Note that, in this framework, uniform limit dominance does not require the assumption of a large market player present in Goldstein and Pauzner (2005), De Groot (2021) or Allen et al. (2018)

Taken together, equations (8)-(9) imply that when $\omega^* \geq \bar{\omega}$, all the banks that fail do so in morning, i.e. $F(\omega^*) = F(\tilde{\omega})$. Furthermore, a mass $F(\omega^*) - F(\bar{\omega})$ of failures affect fundamentally solvent banks. Therefore, the model captures the idea that liquidity defaults can affect fundamentally solvent banks.

The model also incorporates the notion that liquidity failures can effect fundamentally solvent banks, which occurs when $\omega^* < \bar{\omega}$. In this situation, a share of banks $F(\omega^*)$ fail in the morning due to liquidity, whereas a share $F(\tilde{\omega}) - F(\omega^*)$ fail in the afternoon for fundamental reasons. This distinction is crucial for understanding the welfare effects of deposit insurance.

The total resources available for household consumption C correspond to the sum of the ex-post aggregate return on on deposits Π^d, the profits paid by the bank Π^b, and the taxes T paid to the DIA, and are detailed in Appendix A. The total resources available for consumption can be compactly written as

$$C = R_k K_b - \lambda F(\tilde{\omega}) R_k K_b \tag{10}$$

which states that consumption must equal the total return on productive capital net of the dead-weight losses from bank default.

2.6 Results

This section presents three analytical results regarding the welfare properties of the equilibrium and its relationship with deposit insurance policies. The proofs of these results are provided in Appendix A.

The first result is outlined in Proposition 2 below. It states that liquidity failures are inefficient only if the liquidity default threshold ω^* is above the fundamental default threshold $\bar{\omega}$. This result follows from the assumption that the economy's default costs, $(1 - \lambda)$, remain the same regardless of the underlying reason for banks' default. The intuition for this proposition is best understood when considering two sub-cases separately. When $\omega^* \leq \bar{\omega}$, liquidity defaults only affect fundamentally solvent banks and therefore panics do not induce any loss of resources to the economy. In contrast, when $\omega^* > \bar{\omega}$, liquidity failures induce otherwise solvent banks to default, reducing the total resources available to the economy and therefore welfare.

Proposition 2. *Inefficiency*
Let W^* and $\bar{W}$ be the welfare of economies with and without coordination failure among depositors. Then, $\bar{W} > W^*$ if $\bar{\omega} < \omega^*$ and $\bar{W} = W^*$ otherwise.

This result differs from Allen and Gale (1998), who claim that bank-runs can be efficient as long as the gains provided by state-contingency induced by liquidity failures out-weight the costs of defaults. In my framework such state-contingency is already provided by fundamental defaults and therefore liquidity failures can only induce extra default costs relative to the economy without bank-runs. My claim that liquidity defaults can be inefficient is in line with Diamond and Dybvig (1983), Cooper and Ross (2002), and Allen et al. (2018) but extended here to the case of idiosyncratic bank-runs. [8]

Proposition 3 below asserts that increases in deposit insurance coverage reduce the share of banks affected by liquidity-driven defaults. The intuition is that as the share of insured deposits κ increases, households have less incentives to withdraw early and therefore the economy features less bank-runs. A special case of this result is that when $\kappa = 1$ liquidity defaults cannot possibly exist (i.e. ω^*=0). Here, the result extends to the case of partial insurance and idiosyncratic default. As a corollary to Propositions 2 and 3, it follows that increases in deposit insurance can only be welfare improving if liquidity-driven failures affect fundamentally solvent banks, as indicated by Corollary 3.1.

Proposition 3. *Effectiveness of Deposit Insurance*
If $\lambda > 0.5$ and $\exists! \hat{\omega}^* \in [0, \infty)$, then $\frac{\partial \omega^*}{\partial \kappa} < 0$.

[8] De Groot (2021) also considers individual bank defaults for fundamental or through bank-runs, but they find that panics are always inefficient. The reason is that they assume that when a panic occurs, production needs to be carried out inefficiently by bank creditors.

Corollary 3.1. *Welfare and Deposit Insurance*
If $\lambda > 0.5$ *and* $\exists! \hat{\omega}^* \in [0, \infty)$*, then* $\frac{\partial W^*}{\partial \kappa} > 0$ *if* $\omega^* < \bar{\omega}$ *and* $\frac{\partial W^*}{\partial \kappa} = 0$ *if* $\omega^* \geq \bar{\omega}$

The final result of this section examines the relationship between the desirability of deposit insurance and market liquidity. Proposition 4 claims that the minimum deposit insurance needed to recover the social optimum is increasing in market illiquidity λ. The intuition for this result is that as market illiquidity rises, households have stronger incentives to withdraw early, which in turn leads to higher likelihood of liquidity driven defaults.

Proposition 4. *Deposit Insurance and Market Liquidity*
Let κ^* *be the minimum* κ *such that* $\bar{W} = W^*$*, then* $\frac{\partial \kappa^*}{\partial \lambda} < 0$.

To provide further intuition for Proposition 4, consider an economy with illiquidity λ_1 and a level of deposit insurance κ_1 such that the resulting liquidity threshold ω_1^* equals the fundamental threshold $\bar{\omega}_1$. Then, a marginal reduction in market liquidity to $\lambda_2 < \lambda_1$, keeping deposit insurance at κ_1, leads to higher liquidity-default threshold $\omega_2^* > \omega_1^*$. Given that the fundamental default threshold is unaffected by market liquidity (i.e. $\bar{\omega}_1 = \bar{\omega}_2$), it follows that $\omega_2^* > \bar{\omega}_2$, which by Proposition 3 implies $W_2^* < \bar{W}_2$, which is inefficient. Consequently, by Corollary 3.1, a higher deposit insurance coverage (say, $\kappa_2 > \kappa_1$) is necessary to recover the social optimal.

3. Dynamic General Equilibrium

The previous section offered a simple benchmark to link the efficiency properties of bank-runs to the desirability of deposit insurance. Moreover, it illustrated the role played by bank asset liquidity in shaping this relationship. I now embed this framework into am otherwise standard dynamic general equilibrium model. The model is a simplified version of Mendicino et al. (2020), augmented with liquidity-driven default in the style of De Groot (2021).

3.1 Environment

Time is infinite, and each period t is split between morning and afternoon. The economy is populated by a an infinitely lived dynasty, a continuum of banks, a deposit insurance agency and a representative firm.

The dynasty provides consumption insurance across its members, makes a consumption decision, and allocates savings to bank deposits and risky capital. Agents within the dynasty can be either workers or bankers. Workers supply labor inelastically to firms in exchange for wages, while bankers provide equity financing to banks. Bankers directly choose risk-profile of the banks without agency frictions.[9] Each individual banker has a probability θ to become a worker the following period in which case it transfers the profits to the dynasty. This friction prevents bankers' net-worth from growing excessively over time.

The problem of the banks follows the set-up in the partial equilibrium analysis (see Section 2.). Banks invest in capital using bankers equity and demand deposits, face idiosyncratic returns shocks, and operate under limited liability and a capital requirement. Similar to the partial equilibrium analysis, banks default in the morning if the realization of the idiosyncratic returns falls below ω_t^* and default in the afternoon if returns fall below $\bar{\omega}_t$. Given equity is more expensive than deposits, the capital requirement binds. Consequently, bankers' net-worth determines the economy's intermediation capacity.

The behavior of the DIA is is also similar to the partial equilibrium case. When a bank defaults, the DIA takes over the assets of failing banks, liquidates them at fire-sale prices λ_t, pays maximum between the recovery value and the deposit insurance limit, and finances operating losses through taxes. They key difference is that the level of deposit insurance κ_t can change over time depending on the state of the economy.

The representative firm rents out capital, hires labor, produces the final good, and remunerates the owners of production inputs. There are two persistent sources of aggregate

[9] This is different from Gertler and Karadi (2011), where banks can hide funds from bankers.

risk: bank asset risk shocks $\bar{\sigma}_t$ and market liquidity λ_t. Through their effects on bank defaults, these shocks induce fluctuations in bank net worth, which in turn affect production by shifting the economy's intermediation capacity.

The timing of actions is outlined in Table 3. Two timing assumptions are crucial for the analysis of the paper. First, households make their morning withdrawal decisions *after* the realization of aggregate uncertainty. Second, the DIA announces the level of coverage κ_t *after* the realization of aggregate risk, but *before* households make their withdrawal decisions.[10] Together, these assumptions imply that when households make their withdrawal choices, they know both the level of deposit insurance coverage and market prices. Consequently, the coordination game played by households is the same as that in Section 2..

Table 3: Timing of actions

Morning	**Afternoon**
Realization of aggregate shocks (λ_t and $\bar{\sigma}_t$)	Surviving b pay households or default
The DIA announces κ_t	DIA levies taxes and makes payments
Realization of returns (ω_b) and signals ($\hat{\omega}_{h,b}$)	Bankers and workers are remunerated
Each h chooses to withdraw or roll-over	Resources are transferred to the dynasty
If b cannot pay withdrawals it defaults	Dynasty makes decisions

3.2 Production

The representative firm rents out capital K_t, at rental rate $r_{k,t}$, hires labor L_t at price w_t, and produces the final good Y_t using a constant returns to scale technology

$$Y_t = Z K_t^{\alpha} L_t^{1-\alpha} \tag{11}$$

[10]In Section 5.3, this timing assumption about deposit insurance policy will be relaxed.

where Z is normalized to 1, and α represents the capital share in production. The firm's optimality conditions given by

$$w_t = (1-\alpha) Z K_t^{\alpha} L_t^{-\alpha}, \tag{12}$$

$$r_{k,t} = \alpha Z K_t^{\alpha-1} L_t^{1-\alpha}, \tag{13}$$

which require that input prices equal their marginal product.

3.3 Households

The workers are endowed with one unit of labor, $L_t = 1$, which they supply inelastically. Their utility function from consumption $u(C_t)$ features constant relative risk aversion, parametrized by γ. In the afternoon of each period t, the representative household chooses consumption C_t, deposits $D_{h,t+1}$, and capital $K_{h,t+1}$ to maximize future expected utility flows, discounted at rate β. The household's resource constraint is

$$C_t + T_t + D_{h,t+1} + K_{h,t+1} + \Psi(K_{h,t+1}) + \leq w_t L_t + \Pi_t + W_t. \tag{14}$$

The available funds to the household the household are the transfers from workers ($w_t L_t$) and bankers (Π_t) as well as their wealth (W_t) . The uses of resources are given by consumption (C_t), taxes (T_t) as well as savings in deposits ($D_{h,t+1}$) and capital ($K_{h,t+1} + \Psi(K_{h,t+1})$). Household's wealth W_t follows:

$$W_t = \tilde{R}_{d,t} D_{h,t} + R_{k,t} K_{h,t} \tag{15}$$

where $\tilde{R}_{d,t}$ and $R_{k,t}$ are the returns on deposits and capital, respectively. Following Gertler and Karadi (2011), households incur in capital holding costs given

$$\Psi(K_{h,t+1}) = \psi \frac{(K_{h,t+1})^2}{2}. \tag{16}$$

Households can mitigate the drop in banks' intermediation capacity by investing in productive capital, but doing so incurs costs, which are governed by parameter ψ.

3.4 Banks

Each bank operates over two consecutive periods, issues equity $E_{b,t}$ to bankers and offers to households deposits $D_{b,t}$, promising interest rate $R_{d,t}$ to those who roll over their deposits. The banks use these resources to lend $K_{b,t+1}$ to firms. The banks' portfolio yields returns $\omega_{b,t+1} R_{k,t+1}$, where $\omega_{b,t+1}$ represents idiosyncratic bank returns. The banks' budget constraint is given by:

$$E_{b,t} = K_{b,t} - D_{b,t}. \tag{17}$$

Banks are subject to a regulatory constraint $E_t \geq \phi K_{b,t+1}$, which limits the amount of risky investment they can do to a fraction ϕ of their equity. Since equity financing is more costly than deposits, the regulatory constraint binds (see Mendicino et al., 2020), implying that deposits constitute a fraction $1 - \phi$ of risky capital investment:

$$K_{b,t+1} = (1 - \phi) D_{b,t+1}. \tag{18}$$

I now characterize the total profits from banks as a function of bank default. First, consider the case where households are not allowed to withdraw their deposits in the morning (i.e. $p = 0$ for all ω). If no household withdraws, no bank defaults in the morning (i.e.

$\omega^*_{t+1} = 0$), and the bank profits conditional on no withdrawals, denoted $\pi_{t+1|p=0}$ follow:

$$\pi_{t+1|p=0} = \max\left\{\omega_{b,t+1}R_{k,t+1}K_{b,t+1} - R_{d,t}D_{b,t+1}, 0\right\}, \tag{19}$$

where the max operator reflects limited liability. The fundamental default threshold follows $\bar{\omega}_{t+1} = \frac{R^d_{t+1}D_{b,t+1}}{R^k_{t+1}K_{b,t+1}}$, and the expected profits of the bank are given by

$$\mathbb{E}_t\pi_{t+1|p=0} = \mathbb{E}_t\left\{\int_{\bar{\omega}_{t+1}}^{\infty}\left[\omega_{t+1}R_{k,t+1}K_{b,t+1} - R_{d,t+1}D_{b,t+1}\right]dF_{t+1}(\omega_{t+1})\right\}. \tag{20}$$

Now consider the case where $p(\omega_{b,t+1})$ is determined by the coordination game in Section 2.. Proposition 1 states that there exists a unique liquidity threshold ω^*_{t+1} below which the bank fails in the morning (and $p = 1$) and above it the bank survives the morning (and $p = 0$). A full characterization of the determination of ω^*_{t+1} can be found in Appendix B. As discussed in Section 2., when $\omega^*_{t+1} \leq \bar{\omega}_{t+1}$, liquidity defaults materialize on banks that would have failed for fundamental reasons. Therefore, the pay-offs to the banker are given by (19)-(20). However, if $\omega^*_{t+1} > \bar{\omega}_{t+1}$, liquidity defaults affect banks that would be solvent absent runs, and the banks expected profits $\mathbb{E}_t\pi_{t+1}$ are given by:

$$\mathbb{E}_t\pi_{t+1} = \mathbb{E}_t\left\{\pi_{t+1|p=0} - \underbrace{\int_{\bar{\omega}_{t+1}}^{\omega^*_{t+1}}\left[\omega_{t+1}R_{k,t+1}K_{b,t+1} - R_{d,t+1}D_{b,t+1}\right]dF_{t+1}(\omega_{t+1})}_{\text{losses from liquidity failures}}\right\}, \tag{21}$$

where the second term captures the expected profit losses from liquidity-driven defaults.

3.5 Bankers

Bankers are the owners of banks. After receiving the return from their investments, a share θ of bankers become workers, while a share $1-\theta$ of workers become bankers. This assumption keeps the relative mass of workers and bankers fixed, preventing bankers' net worth from growing excessively over time.

3.5.1 Individual Bankers

Each banker starts the period with net-worth $N_{b,t}$, chooses equity investment $E_{b,t}$, dividend payouts $div_{b,t}$, and risk-management effort $e_{b,t}$ to maximize the value to the dynasty. The variance of the idiosyncratic risk borne by banks, denoted $\sigma_{\omega,t+1}$, is given by:

$$\sigma_{\omega,t+1} = \bar{\sigma}_{\omega,t+1} - e_{b,t}, \tag{22}$$

where $\bar{\sigma}_{\omega,t+1}$ is an exogenous time-varying component, and $e_{b,t}$ is the risk-management effort chosen by the banker. The costs of managing risk are given by

$$g(e_{b,t}) = (e_{b,t})^2 R_{k,t+1} K_{b,t+1}, \tag{23}$$

which is increasing an convex in effort and linear in ex-post returns on capital. The bankers' budget constraint is

$$N_{b,t} = E_{b,t} + div_{b,t}. \tag{24}$$

Equity and dividends are paid upfront, but risk-management costs are contracted at the beginning of the period, and paid at the end of the period.[11] The bankers' future net worth is given by

$$N_{b,t+1} = \int_0^\infty \pi_{t+1}(\omega) dF_{t+1}(\omega) E_{b,t} - g(e_{b,t}), \tag{25}$$

where the first term represents the total return on equity from all the banks and the second term is the cost of risk-management effort. The problem of the banker writes:

$$V_{b,t} = \max_{E_{b,t}, div_{b,t}, e_{b,t}} \{ div_{b,t} + \mathbb{E}_t \Lambda_{h,t} [(1-\theta) N_{b,t+1} + \theta V_{b,t+1}] \} \tag{26}$$

[11] This timing assumption for risk management costs maintains the problem from Section 2., while keeping the bankers' problem linear in net worth.

subject to (22)-(25). Equation (26) reflects that when making their choices at time t bankers account for the pay-offs to the dynasty today ($div_{b,t}$) as well as the the expected continuation value $\mathbb{E}_t\Lambda_{h,t}[(1-\theta)N_{b,t+1}+\theta V_{b,t+1}]$. This continuation value accounts for two outcomes: (1) with probability θ, the banker exits, becomes a worker, and transfers resources $N_{b,t+1}$ to the dynasty; and (2) with probability $1-\theta$ the banker continues to operate and has value $V_{b,t+1}$.

Guessing that bankers choose to pay no dividends (i.e. $div_{b,t}=0$), and using the bankers' budget constraint (24), and the leverage constraint of banks (18), the bankers' expected future net-worth simplifies to

$$\mathbb{E}_t N_{b,t+1} = \mathbb{E}_t\Big\{[H(\tilde{\omega}_{t+1}) - F(\tilde{\omega}_{t+1})\bar{\omega}_{t+1} - e_{b,t}^2]\phi R_{k,t+1}N_{b,t}\Big\} \tag{27}$$

where, $\tilde{\omega}_{t+1}$ is the effective default threshold, $H(\tilde{\omega}_{t+1})$ are the expected idiosyncratic returns on performing banks, and $F(\tilde{\omega}_{t+1})$ is the mass of performing banks.

The effort choice $e_{b,t}$ affects future bank net-worth through three channels. First, there is a direct cost of effort through the implementation costs $g(e_{b,t})$. Second, there is an indirect effect through expected idiosyncratic returns revenues from performing banks $H(\tilde{\omega})$. Third, effort affects deposit rates which in turn determine the debt-servicing costs, $F(\tilde{\omega})\bar{\omega}$. Bankers optimal choice of risk-management considers these factors to maximize future expected profits. The detailed derivation of the choice of effort is provided in Appendix B.

Let $v_{b,t}$ represent the bankers' value per unit of wealth. Following Gertler and Karadi (2011) and Mendicino et al. (2020), I guess that the value function of the banker is linear in net-worth, implying $V_{b,t}=v_{b,t}N_{b,t}$. The bankers' value of equity writes:

$$v_{b,t} = \mathbb{E}_t\{\Lambda_{h,t}[(1-\theta)+\theta v_{b,t+1}]R_{E,t+1}\}, \tag{28}$$

where $R_{E,t+1}$ denotes the return on bank equity. As long as $\nu_{b,t}>1$, it is optimal for bankers to invest all their wealth in bank equity and pay no dividends.[12] That is, bankers optimal choices are $div_{b,t} = 0$ and $E_{b,t} = N_{b,t}$.

3.5.2 Bankers' Aggregation

Since bankers invest in a diversified portfolio of banks, they are ex-post identical. Moreover, as the pay no dividends, the law of motion of bankers' aggregate net-worth is given by

$$N_t = \theta R_{E,t} N_{t-1} + \iota \tag{29}$$

where ι denotes the start-up funds of new bankers. The net transfers from bankers to households Π_t are given by:

$$\Pi_t = (1 - \theta) R_{E,t} N_{t-1} - \iota. \tag{30}$$

3.6 Deposit Insurance Agency

The DIA takes over the assets of defaulting banks, and fire-sales them at price λ_t, generating total inflows Π_t^{DIA}. Moreover, the outflows from the DIA, denoted Θ_t^{DIA}, correspond to the deposit insurance payments from failed banks. These payments follow the same structure as the partial equilibrium model: depositors of each bank the maximum between the deposit insurance limit κ_t, and the recovery value of banks. The DIA finances operational losses trough lump-sum taxes, given by $T_t = \Theta_t^{DIA} - \Pi_t^{DIA}$. Appendix B.3 provides further details.

3.7 Interest Rate on Deposits

Households' realized return on deposits $\tilde{R}_{d,t}$ depends on the promised interest rate payments $R_{d,t}$ from performing banks, and payments they receive from defaulting banks. The latter depend on both the deposit insurance payments and the early payments from queue. Absent

[12] After solving the model, I verify this condition indeed holds.

deposit insurance, larger expected bank default rates require a higher promised interest rate on deposits, since households make large losses from defaulting banks. Larger deposit insurance coverage increases the depositors payments from defaulting banks, reducing the sensitivity of required interest rates to default risk. Appendix B.3 provides further details.

3.8 Aggregate Risk

The model features two persistent sources of aggregate uncertainty: a bank risk shock $\bar{\sigma}_t$ and a shock to bank asset liquidity λ_t. For simplicity, I assume that each of these shocks follow a Markov-chain process, represented as

$$P_{\bar{\sigma}} = \begin{pmatrix} 1 - P^{\bar{\sigma}}_{g,b} & P^{\bar{\sigma}}_{g,b} \\ P^{\bar{\sigma}}_{b,g} & 1 - P^{\bar{\sigma}}_{b,g} \end{pmatrix} \tag{31}$$

and

$$P_{\lambda} = \begin{pmatrix} 1 - P^{\lambda}_{g,b} & P^{\lambda}_{g,b} \\ P^{\lambda}_{b,g} & 1 - P^{\lambda}_{b,g} \end{pmatrix} \tag{32}$$

where for each each shock $j \in \{\lambda, \bar{\sigma}\}$, the parameter $P^{j}_{g,b}$ is the probability of transitioning from the "good" to the "bad" state, while $P^{j}_{b,g}$ represents the probability of transitioning from the "bad" to the "good" state. For each shock j, the values of the variables are $[j_g, j_b]$.

3.9 Equilibrium

Appendix B provides the full set of model equations as well as the equilibrium definition. To provide further intuition about the sources of inefficiency in the model, I outline here the goods market clearing condition, given by

$$Y_t = \underbrace{C_t}_{\text{consumption}} + \underbrace{X_t}_{\text{investment}} + \underbrace{\Psi(K_{h,t+1})}_{\text{holding costs}} + \underbrace{\lambda_t F(\tilde{\omega}_t) R_{k,t} K_{b,t}}_{\text{default costs}} + \underbrace{g(e_t) R_{k,t} K_{b,t}}_{\text{risk-management costs}} . \tag{33}$$

This equation states that total resources should be used to pay for consumption, investment, as well as the costs from household capital holding, bank default, and bank risk-management. Deposit insurance affects total resources available for consumption through all these channels.

In the model, fluctuations in bank asset liquidity, λ_t, push the economy into periods where total bank defaults are driven be liquidity failures $F(\omega_t^*) \geq F(\bar{\omega}_t)$ or fundamental default $F(\omega_t^*) < F(\bar{\omega}_t)$. The interaction of liquidity-driven defaults and potentially state-contingent deposit insurance induces non-linear dynamics. To account for this model feature, I implement a global solution method in the spirit of Elenev et al. (2021).

4. Quantitative Analysis

This section provides details on the model calibration, and compares effects of liquidity and fundamental banking crises on real economic activity.

4.1 Calibration

The model is calibrated at a quarterly frequency to capture key features of the US economy over the period 1970Q1-2022Q4. Standard parameters are set following the calibration strategy in the literature. The parameters governing the aggregate risk processes are specific to my model. Table 4 presents the model parameters, while Table 5 compares the model's fit to the corresponding data targets.

Standard Parameters. I set the capital share in production, α, to 0.33 and the capital depreciation, δ , to 0.02. To match an average annual risk-free interest rate of 2%, I set the discount factor , β, to 0.995. I assume $\gamma = 1$ corresponding to log-utility. Following Gertler and Karadi (2011), I set $\theta = 0.972$, which implies a bankers' exit of probability of 2.8 %. The bank capital requirement , ϕ , is set to 8 % in accordance with Basel I and Basel II frameworks. I set $\kappa = 0.623$, reflecting the 2008 deposit insurance level, which covered

62.3 % of total deposits.[13] I calibrate ψ and ι and following the strategy of Mendicino et al. (2020). I set the households' capital holding costs to $\psi = 0.001$, in order to match the US household share in domestic corporate debt markets reported by Elenev et al. (2021). The model delivers a value of 14.29 %, slightly above the data value of 13.7 %. I set $\iota = 0.001$ to align the model's average annual return on bank equity with the data. The model produces a return of equity of 11.46 %, close to the data value of 11.14 %.

Aggregate Risk Parameters. To calibrate the parameters of the exogenous processes, I use as targets several stylized facts about US banking crises. I classify U.S. banking crises as either liquidity or fundamental, based on Baron et al. (2021), and combine this with FDIC data on asset-weighted failure rates for U.S. commercial banks. This data allows me to compute a series of moments regarding the probability, persistence, and severity of each crisis type.

I use natural years as the model level of observation, categorizing them in "no-crises" years ($\lambda = \lambda_g$ and $\bar{\sigma} = \bar{\sigma}_g$ for all quarters), "fundamental crises" years ($\lambda = \lambda_g$ for all quarters and $\bar{\sigma} = \bar{\sigma}_b$ for at least one quarter) and "liquidity crises" years ($\lambda = \lambda_b$ for at least one quarter). This classification is consistent with the definitions in Baron et al. (2021).[14]

The process for λ is calibrated as follows. First, I set the quarterly probability of transitioning to the bad liquidity state to $p^{\lambda}_{g,b} = 1.13\%$ in order match the probability of transitioning to a "liquidity crises" year conditional on being in a "no crises" year. I get a model moment of 4.50 % compared to a data moment of 4.55 %. Second, I set the quarterly probability of exiting the bad liquidity state $p^{\lambda}_{b,g}$ to match the unconditional probability of observing a "liquidity crises" year, with the model delivering a value of 7.64 % relative to a data value of 7.55 %. Third, I choose the bad realization of the liquidity state, $\lambda_b = 40.59$

[13] Since the largest contribution to average liquidity default in the sample stems from the 2008 crises, choosing the 2008 level of coverage is reasonable. This value is below the long-run average of the insured deposits share of around 0.70 %.

[14] Baron et al. (2021) use yearly data, and classify an observation as panic-driven, if there where narrative descriptions of bank-runs in the newspapers. See data Appendix for further details.

Table 4: Model Parameters

Description	Parameter	Value (%)
Production		
Capital Share in Production	α	33
Capital Depreciation Rate	δ	2
Households		
Discount Factor	β	99.5
Capital Holding Costs	ψ_h	0.05
Risk Aversion	γ	1
Banks		
Banker Exit Probability	$1-\theta$	2.8
Banker Start-up Equity	ι	0.05
Bank Capital Requirement	ϕ	8
Share of Insured Deposits	κ	62.3
Aggregate Risk		
Fundamental Crises Entry Prob.	$p^{\bar{\sigma}}_{g,b}$	1.14
Fundamental Crises Exit Prob.	$p^{\bar{\sigma}}_{b,g}$	12.50
Exogenous Bank Risk (good times)	$\bar{\sigma}_g$	5.09
Exogenous Bank Risk (bad times)	$\bar{\sigma}_b$	6.74
Liquidity Crises Entry Prob.	$p^{\lambda}_{g,b}$	1.13
Liquidity Crises Exit Prob.	$p^{\lambda}_{b,g}$	25.00
Bank Asset Liquidity (good times)	λ_g	43.00
Bank Asset Liquidty (bad times)	λ_b	40.59

Notes: This table reports the model parameters of the baseline economy. The parameters ψ, ι,$p^{\bar{\sigma}}_{g,b}$, $p^{\bar{\sigma}}_{b,g}$, $\bar{\sigma}_g$, $\bar{\sigma}_b$, $p^{\lambda}_{g,b}$, $p^{\lambda}_{b,g}$, λ_g, λ_b are calibrated internally. For an assessment of the model fit, see Figure 5. The remainder parameters are either standard in the literature of have direct data counter-parts. See main text for a detailed description of the calibration strategy.

%, yielding an average default rate in a "liquidity crises" year of 4.18 %, slightly below the 4.25 % observed in the data. Finally, I set $\lambda_g = 43.00$ % to align with average recovery value from defaulting assets reported by Bennett and Unal (2015). The model delivers a recovery value of 46.89 %, which stands substantially bellow the 66.82 % in the data.[15]

I apply the same strategy to calibrate the bank-risk process $\bar{\sigma}$. First, I set the quarterly probability entering the bad fundamental risk state $p^{\bar{\sigma}}_{g,b}$ to 1.14 %, targeting the probability

[15]I compute the average recovery rate following De Groot (2021).

Table 5: Model Fit

Description	Data (%)	Model (%)
Average Household Capital Share	13.7	14.29
Average Bank Equity Return	11.14	11.46
Average Recovery Value on Defaulting Banks	66.82	46.89
Probability of Transitioning to Fundamental Crises	4.55	4.32
Unconditional Fundamental Crises Probability	11.32	10.55
Average Bank Default in Fundamental Crises	1.89	1.92
Probability of Transitioning to Liquidity Crises	4.55	4.5
Unconditional Liquidity Crises Probability	7.55	7.64
Average Bank Default in Liquidity Crises	4.25	4.18

Notes: This table compares the data targets with the model moments with the parameters reported in Table 4. The moments are computed using the simulated model over 250,000 quarters. All model and data targets are expressed in % and in annual terms. This default data is collected from the FDIC, and the crises classification follows Baron et al. (2021). The moment on household capital share is from Elenev et al. (2021), the bank recovery rates are from Bennett and Unal (2015). I refer the reader to the data Appendix for further details.

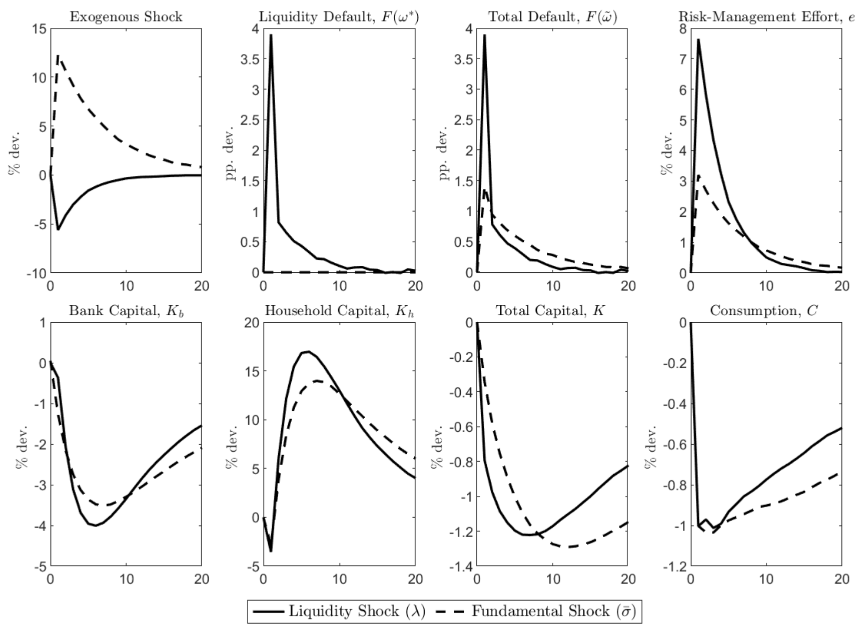
of transitioning to a fundamental crises, yielding at model value of 4.32% compared to 4.55 % in the data. Second, I set $p^{\bar{\sigma}}_{b,g}$=25.50 %, producing an unconditional probability of a fundamental crises of 7.64 %, close to the 7.55 % in the data. Third, I set $\bar{\sigma}_b = 6.74$ %, resulting in an average default rate in a "fundamental crises" years of 1.92 % versus a value of 1.89 % in the data. Finally, I set $\bar{\sigma}_g = 5$ % to get no defaults occur in the good aggregate state.

4.2 Banking Crises

This subsection conducts a series of exercises to illustrate how banking crises propagate to the real economy through the lenses of the calibrated model. To facilitate comparison across crises types, I simulate fundamental and liquidity crises to deliver the same impact effect on consumption.

Fundamental Crises. The black dashed line in Figure 2 illustrates the effect of a persistent shock to bank asset risk $\bar{\sigma}$, following the approach of Mendicino et al. (2020). The deterioration on bank assets risk leads to a sharp rise in total bank default rates on impact. However, as the second panel shows, liquidity-driven defaults are unaffected. This crises is fundamentally-driven in the sense that all the rise in bank defaults is a result of banks choosing to default due to poor returns.

Figure 2: Fundamental and Liquidity Banking Crises



Notes: This figure shows the impulse response function (IRF) of a fundamental shock (black solid line) and a liquidity shock (red-dotted line) of the calibrated model. The simulation starts at ergodic mean of the economy conditional on being in the good aggregate state. At $t = 1$, the baseline path assumes the good realization of both shocks. For a liquidity crises path, I set $\lambda_t = \lambda_b$. For the fundamental crises path, I set $\bar{\sigma}_t = \bar{\sigma}_b$ for the a share of observation that delivers the same impact response in consumption than a liquidity crises. From $t = 2$ onwards, I simulate the economy 10,000 times for a total of 25 periods, and average across simulations. Variables are expressed in percent deviations from the no crises path, except default rates which are expressed in percentage points deviations.

Following the shock, banks intensify their risk-management effort to decrease future default risk. Since portfolio adjustment is costly, banks choose to mitigate, rather than eliminate this risk. Bank defaults reduce the banking sector's holdings of productive capital, which, alongside a reduction in household capital holdings, causes a contraction in total capital. This drop in economic activity, in turn, feeds back into bank default. In fact, even though the exogenous bank risk fades out sharply after the initial impact, total bank default remains elevated for two more quarters.

The real effects of the banking crises are persistent for two main reasons. First, since banks are at the regulatory constraint, the only way they can increase their lending capacity is through retained earnings, which accumulate slowly. Second, households increase their direct lending to productive firms. Since they are inefficient at doing so, the recovery in total capital reaches a trough after 12 quarters. Together, these two forces contribute to a highly persistent drop in consumption.

Liquidity Crises. The black solid line in Figure 2, shows the effects of a persistent reduction in bank asset liquidity, λ, and is similar to the simulations in De Groot (2021). The decline in bank asset liquidity induces households to withdraw their deposits early from the banks, leading to a sharp increase liquidity defaults. This event constitutes a liquidity crises as the rise in total bank defaults is entirely attributed to liquidity-driven defaults.

The rest of the dynamics of liquidity crises are qualitatively similar to fundamental crises: banks increase their risk management effort to reduce default risk, and there is a persistent drop in both total capital and consumption. Quantitatively, however, the model predicts that the effect of liquidity-driven crises on real economic activity are substantially less persistent than those from fundamentally driven crises. During a liquidity crises the trough in total capital materializes around 6 quarters earlier than during fundamental crises. As will become clear later, the low persistence of liquidity crises has important implications for deposit insurance design.[16]

[16]The low persistence of liquidity driven crises is not surprising in light of the calibrated parameters. This calibration reflects the fact that, as illustrated in Figure 1, the only fundamental crises in my sample is the 1990s crises, which lasted much longer than the rest of panic-driven crises.

5. Assessing Deposit Insurance Reforms

This section assesses different options for deposit insurance reform by performing counterfactual exercises through the lenses of the calibrated model. I consider the implications of fixed and state-contingent deposit insurance for long-run outcomes and banking crises.

5.1 Fixed Deposit Insurance

I begin the analysis by studying the effects of changes fixed deposit insurance. In particular, I assume that $\kappa_t = \kappa$ for all periods, and study the implications of changes in κ.

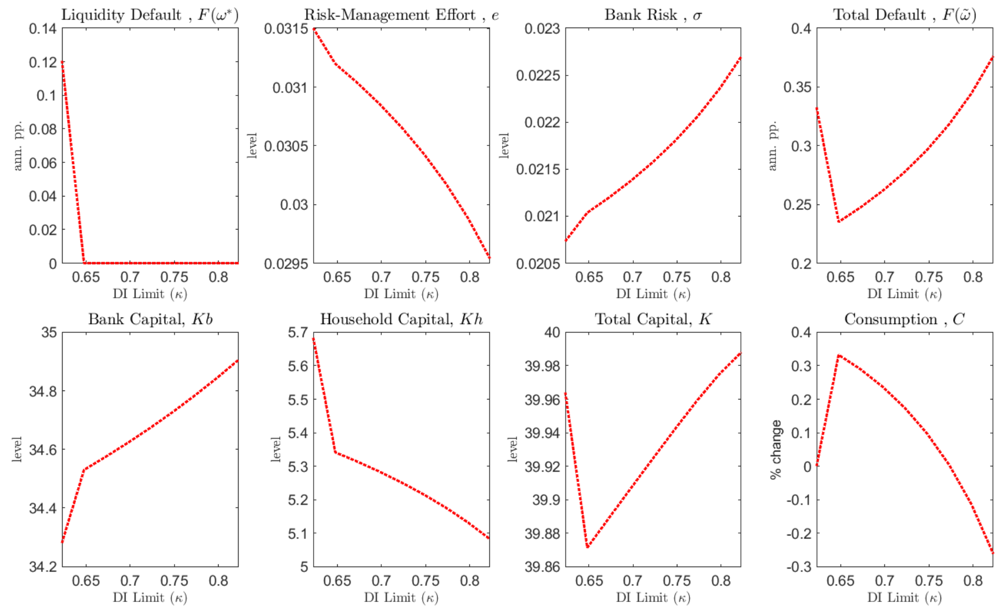
5.1.1 Long-run Outcomes

I start by displaying in Figure 3 the long-run averages of economies with different values of fixed ex-ante deposit insurance limits κ.

As illustrated by the first panel, increases in DI coverage lead to a a drop in liquidity-driven defaults, which results from two opposing forces. On one hand, similarly to Proposition 3, increases in κ lead to a reduction in the liquidity default threshold ω^*. One the other, increases in κ lead banks to reduce their risk-management effort resulting in more risk in bank portfolios which absent changes in ω^*, would lead to more morning defaults. It turns out that the former effect quantitatively dominates the latter. Therefore, the result in Proposition 3 carries through to the dynamic equilibrium framework. That is, despite the presence of moral hazard an increase in deposit insurance coverage to 65 % completely prevents liquidity-driven defaults.

However, as illustrated by the bottom left panel, beyond $\kappa = 65$ % further increases in deposit insurance leads to a rise in total default rates. This result is in stark contrast with the partial equilibrium analysis presented in Section 2.6. In partial equilibrium, the fundamental threshold ($\bar{\omega}$) and the riskiness of bank assets (σ) was fixed ex-ante. In general

Figure 3: The Long-Run Effects of Fixed Deposit Insurance



Notes: This figure shows the long-run averages of selected variables under different levels of Fixed Deposit Insurance. The averages are taken over a simulated series of 250,000 periods. Default rates are expressed in annual percentage points (ann. pp.), consumption is reported in percentage changes from the baseline economy with $\kappa = 62.3$ %, and the remaining variables are reported in levels.

equilibrium, changes in κ lead to large increases in bank risk-taking which results in higher fundamental and total default rates as κ increases further.

The size of the banking sector is increasing in the level of deposit insurance coverage, but the strength of this relationship changes at $\kappa = 65$ %. For levels below 65 %, higher coverage is associated with a decrease in both total defaults and costly risk-management effort. These two forces lead to a strong increase in bank capital. Beyond that level, higher κ leads to an increase in defaults resulting in a smaller increase in bank capital. Households choose to hold less capital resulting in only small changes to total capital accumulation despite larger capital holdings by banks. Since household capital holdings are costly to society, higher deposit insurance improves the overall efficiency in capital intermediation.

The interaction of bank capital and default channels leads to an optimal level of consumption at $\kappa = 65\%$. Below that level, increases in coverage lead both to both a larger banking sector and less dead-weight losses, which result in an increase in consumption. Above that level, consumption is decreasing in deposit insurance coverage for two reasons. First, the increase in default rates is associated with larger dead-wight losses, which, all else equal, leads to a reduction in the resources available for consumption. Second, the increase in capital accumulation becomes weaker, which results in a smaller increase in total production.

5.1.2 Stabilization Effects

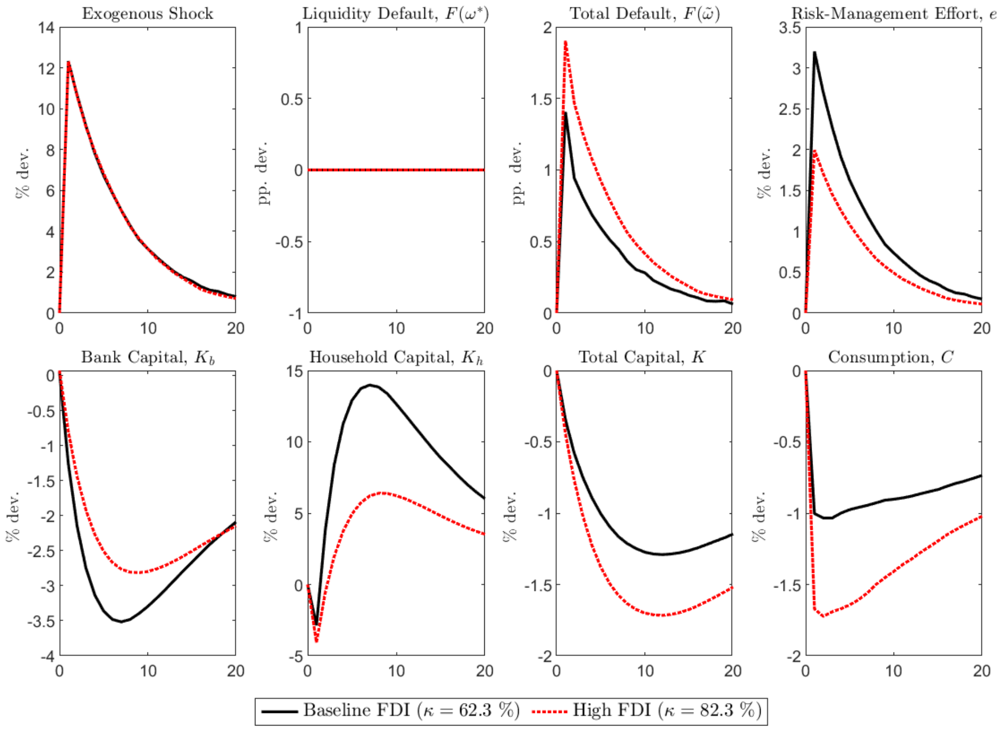
This section provides results on the implications of fixed ex-ante deposit insurance for fundamental and liquidity-driven banking crises.

Fundamental Crises. Figure 4 compares the effects of fundamental crises in the baseline economy ($\kappa = 62.3$ %) with a higher level of coverage ($\kappa = 82.3$ %).[17] The key message is that higher deposit insurance leads to more severe fundamental crises. The reason is that higher ex-ante coverage induces moral hazard and leads banks to have riskier portfolios ex-ante. As a result, when the fundamental crises hits, bank default increases by more on impact. After the initial hit, higher coverage induces banks to exert less risk-management effort ex-post, which explains why bank capital drops by less despite a stronger increases in defaults. However, the sharper increase in bank defaults reduces households' resources to invest. This leads to a much sharper drop in household capital investment, which in turn results in a larger drop in total capital under higher deposit insurance. Together, the increase in bank defaults and total capital result in a sharper drop in consumption.

Liquidity Crises. Figure 5 compares the effects of liquidity crises in the baseline economy ($\kappa = 62.3$ %) with a higher level of coverage ($\kappa = 82.3\%$). The figure provides a stark result: higher deposit insurance completely eliminates liquidity crises. By reducing the incentives of households to withdraw, deposit insurance can completely prevent the increase in liquidity driven defaults. Since all the increase in total defaults is driven by liquidity

[17] This increase in the share of insured deposits corresponds to the increase approved in 2008, which lifted the limit from 100,000 to 250,000 dollars.

Figure 4: Fixed Deposit Insurance and Fundamental Crises



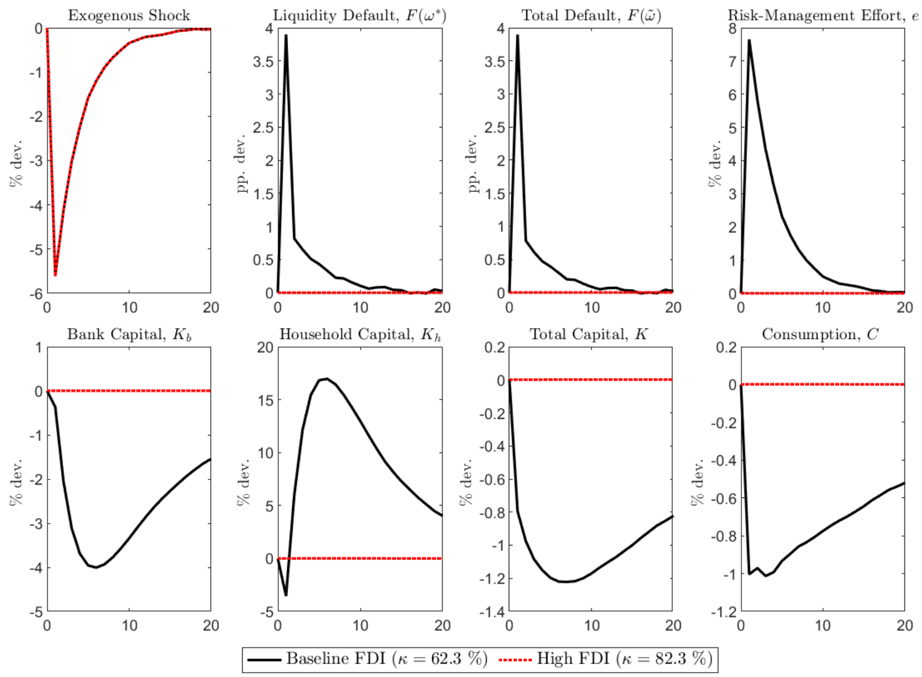
Notes: This figure shows the impulse response function (IRF) of a fundamental shock ($\bar{\sigma}_t$) under the baseline FDI of 62.3 % (black solid line), and a higher FDI level of 82.3 % (red dotted line). The simulation starts at ergodic mean of the economy conditional on being in the good aggregate state. At $t = 1$, the baseline path assumes the good realization of both shocks, and for the fundamental crises path, I set $\bar{\sigma}_t = \bar{\sigma}_b$. From $t = 2$ onwards, I simulate the economy 10,000 times for a total of 25 periods, and average across simulations. Variables are expressed in percentage from the no crises path, except default rates which are expressed in annual percentage points deviations.

defaults, there is no change in aggregate defaults. As a result, a liquidity shock does not have any effects on real economic activity: total capital and consumption are unchanged.

5.2 Fast State-Contingent Deposit Insurance

This section examines the implications of state-contingent deposit insurance for long-run outcomes and banking crises. In these model exercises, I assume that in adverse aggregate states (i.e. $\bar{\sigma} = \bar{\sigma}_b$ and $\lambda = \lambda_b$) the government can observe the shock and increase the

Figure 5: Fixed Deposit Insurance and Liquidity Crises



Notes: This figure shows the impulse response function (IRF) of a liquidity shock (λ_t) under the baseline FDI of 62.3 % (black solid line), and a higher FDI level of 82.3 % (red dotted line). The simulation starts at ergodic mean of the economy conditional on being in the good aggregate state. At $t = 1$, the baseline path assumes the good realization of both shocks, and for the liquidity crises path, I set $\lambda_t = \lambda_b$. From $t = 2$ on, I simulate the economy 10,000 times for a total of 25 periods, and average across simulations. Variables are expressed in percentage from the no crises path, except default rates which are expressed in annual percentage points deviations.

coverage to a level $\kappa_H \geq 62.3\%$, *before* households withdraw. I keep the level of deposit insurance for all the other realizations of exogenous shocks at the baseline level $\kappa = 62.3\%$. This policy mirrors the type of ex-post increases in deposit insurance that were implemented during recent US banking crises, under the assumption of fast government response.

5.2.1 Long-Run Outcomes

Figure 6 shows the long-run averages of economies with different levels of state-contingent deposit insurance, and compares them with the case of fixed ex-ante deposit insurance policy.

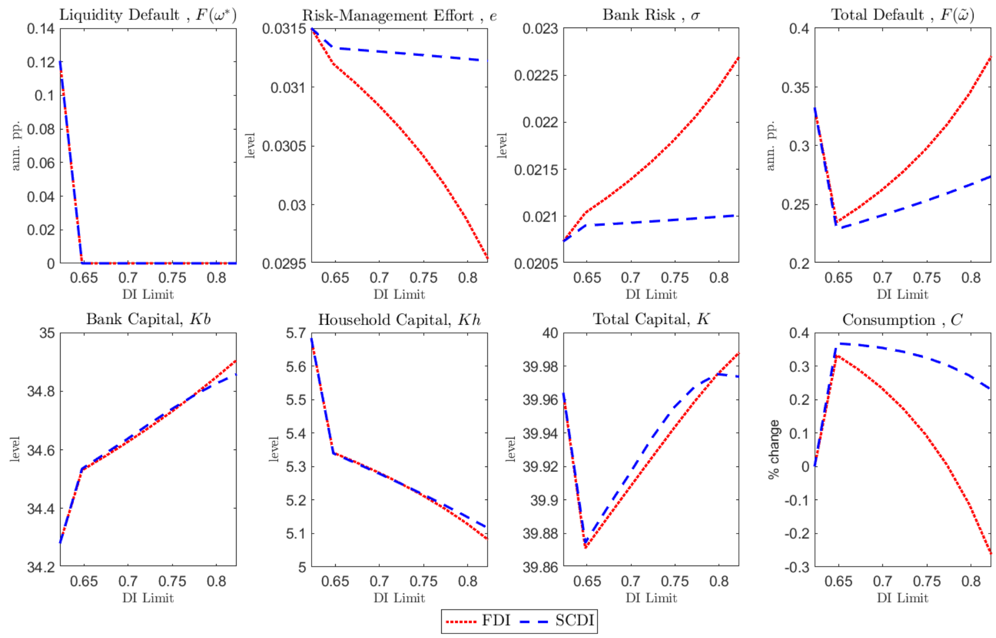
Qualitatively, both state-contingent (dashed blue line) and fixed (dotted red line) deposit insurance work in a similar way. Both policies are successful at reducing liquidity driven defaults, induce lower risk-management effort and riskier bank portfolios. In both cases total defaults are lowest at $\kappa = 65\%$ and bank capital accumulation is increasing in the level of coverage.

However, there are important quantitative differences between both policies. Relative to the fixed deposit insurance regime, the state-contingent policy induces less moral hazard, as illustrated by a smaller increase in bank risk. This difference has two important implications. First, the state-contingent policy initially leads to a stronger reduction in total bank defaults than fixed deposit insurance. Second, increase in fundamentally driven defaults for levels of deposit insurance above 65 % is much smaller under the state-contingent policy.

The effects of both policies on the size of the banking sector are quantitatively small. This result arises from the interaction of two opposing forces. On one hand, increases in fixed deposit insurance lead to a larger decrease in risk-management effort, reducing the operating costs of banks. On the other, the state-contingent policy is associated with lower bank default rates resulting in a larger banking sector. Ultimately, these two forces roughly off-set each other, resulting in small differences in bank capital accumulation. Likewise, both policies produce similar changes in both household capital holding and total capital accumulation.

Since the state-contingent policy contains moral hazard relative to the fixed policy, it leads to lower dead-weight losses to society, and consequently larger average consumption. In fact, increasing the coverage to 65% only in adverse times, increases consumption by 10% more than increasing coverage to 65% permanently. This result rationalizes that current US practice of increasing deposit insurance only in crises times.

Figure 6: The Long-Run Effects of State-Contingent Deposit Insurance



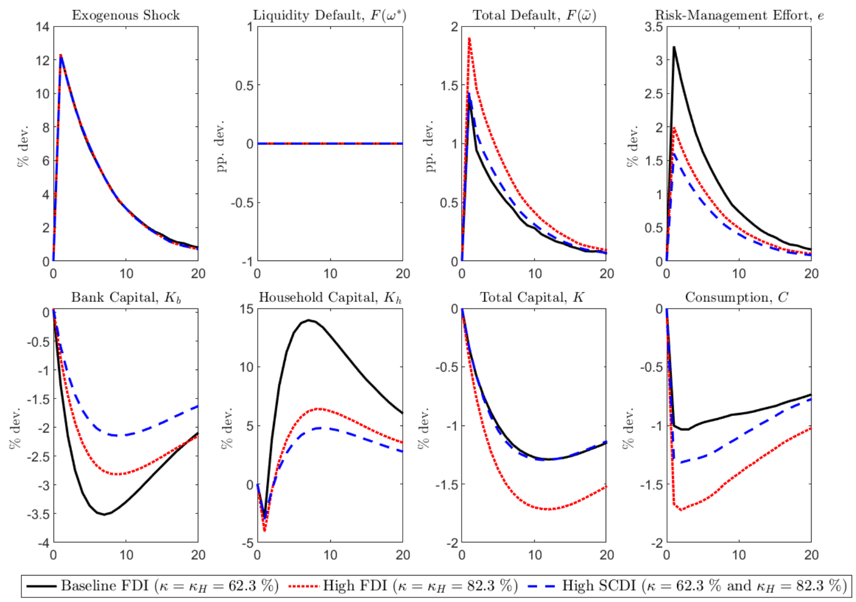
Notes: This figure shows the long-run averages of selected variables. For Fixed Deposit Insurance (red dotted line) the level of DI coverage is kept constant over time. For State Contingent Deposit Insurance (blue dashed line), the level of DI coverage is fixed at baseline level during good times, and is increased in bad times. The averages are taken over a simulated series of 250,000 periods. Default rates are expressed in annual percentage points (ann. pp.), consumption is reported in percentage changes from the baseline economy with FDI of $\kappa = 62.3$ %, and the remaining variables are reported in levels.

5.2.2 Stabilization Effects

Next, I evaluate how state-contingent deposit insurance affects banking crises, providing further support for the view that increasing deposit insurance only in crises times is preferable to permanent increases.

Fundamental Crises. Figure 7 illustrates the effects fundamental crises under state-contingent deposit insurance ($\kappa = 62.3\%$ and $\kappa_H = 82.3$ %), compared to the baseline model ($\kappa = 62.3\%, \kappa_H = 62.3$ %) and high fixed deposit insurance ($\kappa = \kappa_H = 82.3$ %). As the figure shows, the state-contingent policy (dashed blue) leads to less severe fundamental crises than fixed DI increases (dotted red). Specifically, the increase in fundamentally driven defaults

Figure 7: State-Contingent Deposit Insurance and Fundamental Crises



Notes: This figure shows the impulse response function (IRF) of a fundamental shock ($\bar{\sigma}_t$). The black line plots the case of a baseline FDI of 62.3 % while the red dotted line plots a high level of FDI of 82.3 %. The blue dashed line shows the case where the level of coverage is fixed at 62.3 % during good times, and to of 82.3 % during bad times. The simulation starts at ergodic mean of the economy conditional on being in the good aggregate state. At $t = 1$, the baseline path assumes the good realization of both shocks, and for the fundamental crises path, I set $\bar{\sigma}_t = \bar{\sigma}_b$. From $t = 2$ onwards, I simulate the economy 10,000 times for a total of 25 periods, and average across simulations. Variables are expressed in percentage from the no crises path, except default rates which are expressed in annual percentage points deviations.

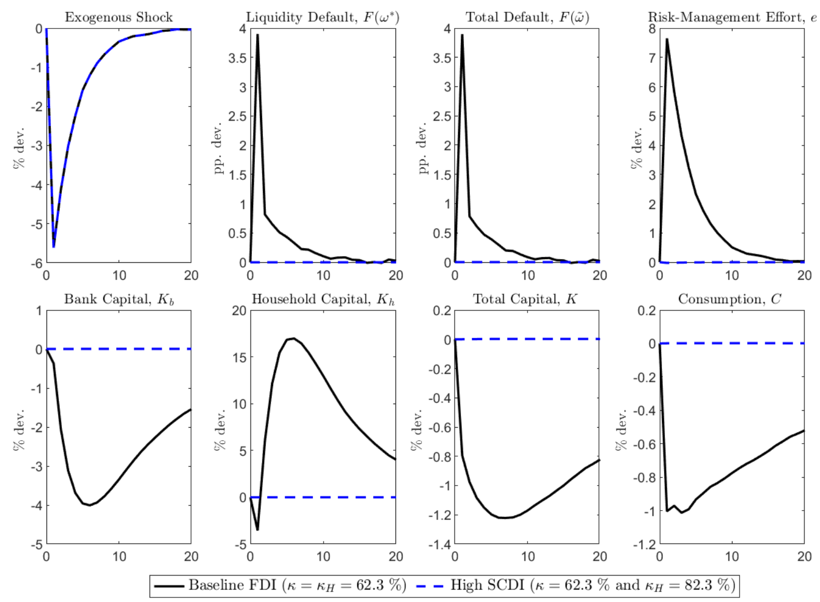
is substantially lower than under the high fixed deposit insurance. The ex-post increase in coverage also leads to a smaller increase in risk-management effort.

The combination of lower default rates and a smaller increase in risk management, results in a much smaller fall in both bank capital and total capital. As a result, total consumption falls by less under the state-contingent policy. However, the state-contingent policy does no fully eliminate the moral hazard costs of DI since fundamental crises are still stronger than in the baseline economy (black line).

Liquidity Crises. Figure 8 compares the effects liquidity crises under state-contingent deposit insurance ($\kappa = 62.3\%, \kappa_H = 82.3$ %), with the baseline model ($\kappa = 62.3\%, \kappa_H = 62.3$

%). The main message from this figure is that increasing deposit insurance in during bad times is as effective as ex-ante increases at preventing liquidity crises. By increasing the deposit insurance limit before households make their withdrawal decisions, the government can prevent the crises. Consequently, as long as the government implements the coverage increase promptly, it can fully avert the liquidity crises.

Figure 8: State-Contingent Deposit Insurance and Liquidity Crises



Notes: This figure shows the impulse response function (IRF) of a liquidity shock (λ_t). The black line plots the case of a baseline FDI of 62.3 %. The blue dashed line shows the case where the level of coverage is fixed at 62.3 % during good times, and to of 82.3 % during bad times. The simulation starts at ergodic mean of the economy conditional on being in the good aggregate state. At $t = 1$, the baseline path assumes the good realization of both shocks, and for the liquidity crises path, I set $\lambda_t = \lambda_b$. From $t = 2$ on, I simulate the economy 10,000 times for a total of 25 periods, and average across simulations. Variables are expressed in percentage from the no crises path, except default rates which are expressed in annual percentage points deviations.

5.3 Slow State-Contingent Deposit Insurance

The assumption that the government can react to crises before the private sector agents make their choices is relatively strong. In reality, several frictions could prevent such a fast government response. First, ex-post increases in coverage often require legal changes, which might be slow to implement. For instance, in 2008, the temporary increase in coverage needed the approval of US Congress, and came into effect over one month after the failure of Washington Mutual. Similarly, the ex-post increases in coverage during the 2023 crises required the approval by the FDIC, Federal Reserve, and US treasury. Second, the government might lack the real time knowledge about the underlying shocks hitting the economy. In fact, evidence suggests that bank-runs might becoming faster, complicating a timely government response.[18] To capture these frictions, I allow the government to implement an increase in coverage at t (i.e. $\kappa_{H,t} \geq 62.3$ %) only if they observed a bad aggregate shock in the previous period (i.e. if $\bar{\sigma}_{t-1} = \bar{\sigma}_b$ and $\lambda_{t-1} = \lambda_b$). For all other realizations of exogenous shocks at the baseline level $\kappa = 62.3\%$.

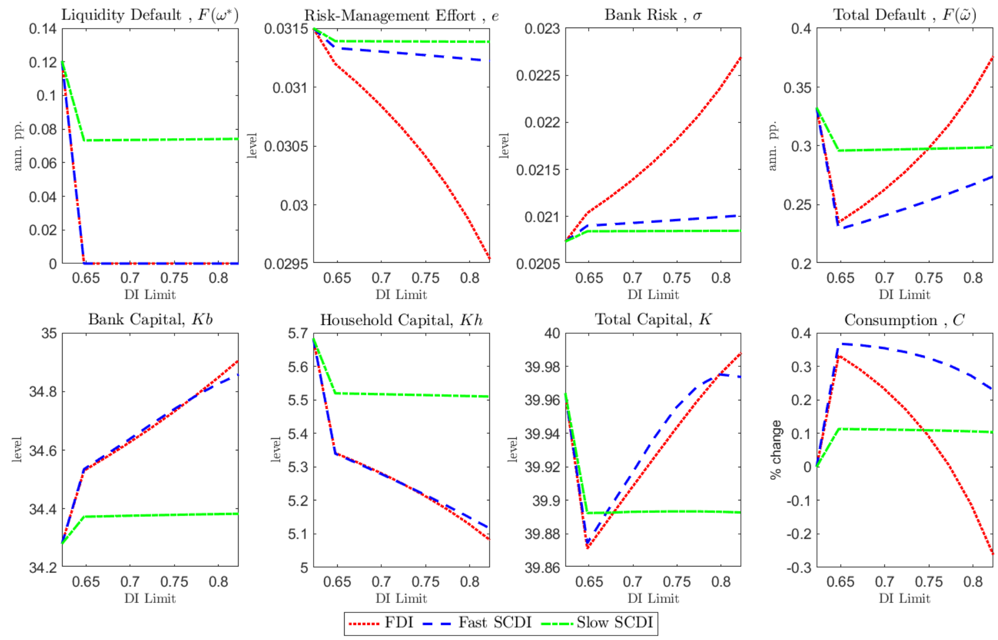
Long-run Outcomes. Figure 9 shows the long-run outcomes for economies with different $\kappa_H \geq 62.3\%$, under slow implementation (green dash-dotted line), compared with fast state-contingent deposit insurance (blue dashed line) and changes in fixed deposit insurance (red dotted line).

The key message from this figure is that slow state-contingent deposit insurance can mitigate liquidity driven failures, but it cannot completely prevent them. Households anticipate that when transitioning from the good aggregate state to a bad liquidity state, the government cannot increase the coverage contemporaneously. As a result, they have strong incentives to withdraw their deposits which forces some banks to default. However, as the liquidity crises persists, the increase in coverage comes into effect and prevents further liquidity defaults moving forward. Quantitatively, this policy can only prevent about 30 % of the liquidity driven defaults. This result differs from the fast state-contingent policy and high fixed deposit insurance, which are enough to completely eliminate liquidity driven failures.

Interestingly, slow state-contingent deposit insurance induces a smaller increase in bank

[18]See FDIC (2023) for a detailed discussion on the underlying factors and Rose (2023) for a comparison of the 2023 banking turmoil with previous bank failures.

Figure 9: The Long-Run Effects of Slow State-Contingent Deposit Insurance



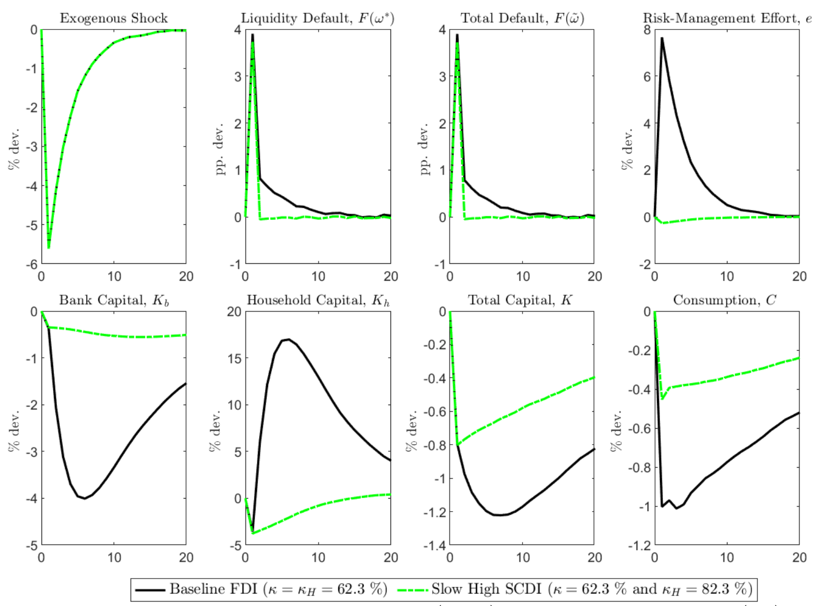
Notes: This figure shows the long-run averages of selected variables. For Fixed Deposit Insurance (red dotted line) the level of DI coverage is kept constant over time. For state-contingent deposit insurance, the level of DI coverage is fixed at baseline level during good times, and is increased in bad times. For Fast State Contingent Deposit Insurance (green dotted-dashed line) the government responds contemporaneously to financial shocks, while for Slow State Contingent Deposit Insurance (green dotted-dashed line) the government responds with a lag. The averages are taken over a simulated series of 250,000 periods. Default rates are expressed in annual percentage points (ann. pp.), consumption is reported in percentage changes from the baseline economy with FDI of $\kappa = 62.3$ %, and the remaining variables are reported in levels.

risk than alternative policies. The reason is that since increases in deposit insurance do not fully eliminate liquidity risk ex-post, banks need to reduce their risk ex-ante risk in order to reduce their cost of debt. As a result, fundamentally driven defaults increase at a much lower rate than under alternative policies. The smaller drop in liquidity defaults, together with a smaller reduction in bank risk management costs imply that both bank capital declines less under the slow implementation of state-contingent limits.

Crucially, the consumption gains from this policy are substantially smaller than under the alternative policy reforms. In particular, the smaller reductions in liquidity failures dominate the smaller increases in fundamentally driven defaults, resulting in stronger dead-weight losses. In fact, the optimal level of slow state-contingent deposit insurance achieves gains that are about 70 % lower than the alternative reforms.

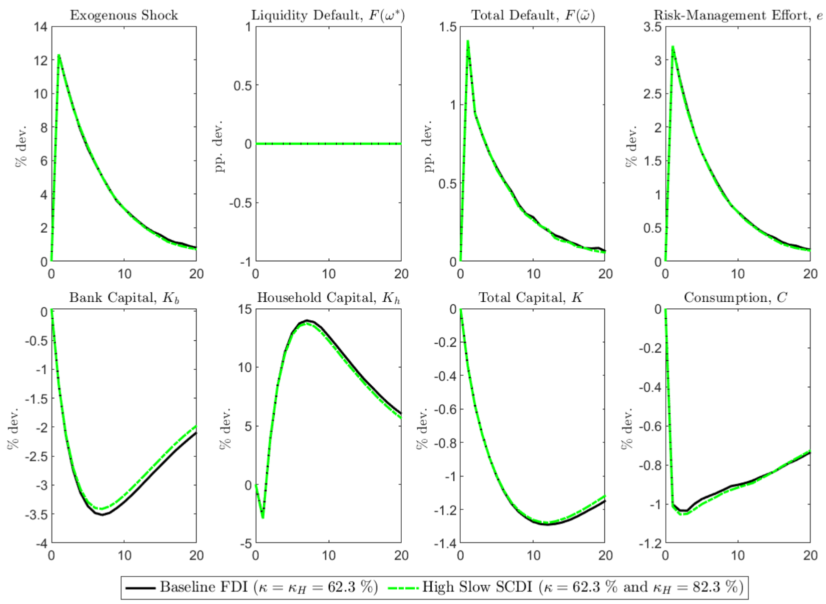
Stabilization Effects. Figure 10 and Figure 11 provide further evidence on dynamics of banking crises under slow state-contingent deposit insurance. Figure 10 illustrates the response to liquidity crises. It shows that when the shock hits (at $t = 1$), liquidity defaults increase, but they converge back to zero thereafter (from $t > 1$) due to the increase in the deposit insurance coverage by the government. This policy reduces drastically the drop in bank capital, but the mitigation in household consumption and investment is smaller. For completeness, Figure 11 shows that, due to the smaller increase in ex-ante risk by banks, the effects of fundamental crises are quantitatively very similar than in the baseline economy.

Figure 10: Slow State Contingent Deposit Insurance and Liquidity Crises



Notes: This figure shows the impulse response function (IRF) of a liquidity shock (λ_t). The black line plots the case of a baseline FDI of 62.3 %. The blue dashed line shows the case where the level of coverage is fixed at 62.3 % during good times, and to of 82.3 % during bad times. The simulation starts at ergodic mean of the economy conditional on being in the good aggregate state. At $t = 1$, the baseline path assumes the good realization of both shocks, and for the liquidity crises path, I set $\lambda_t = \lambda_b$. From $t = 2$ on, I simulate the economy 10,000 times for a total of 25 periods, and average across simulations. Variables are expressed in percentage from the no crises path, except default rates which are expressed in annual percentage points deviations.

Figure 11: Slow State Contingent Deposit Insurance and Fundamental Crises



Notes: This figure shows the impulse response function (IRF) of a fundamental shock ($\bar{\sigma}_t$). The black line plots the case of a baseline FDI of 62.3 %. The green dotted-dashed line shows the case where the level of coverage is fixed at 62.3 % during good times, and to of 82.3 % during bad times. The simulation starts at ergodic mean of the economy conditional on being in the good aggregate state. At $t = 1$, the baseline path assumes the good realization of both shocks, and for the fundamental crises path, I set $\bar{\sigma}_t = \bar{\sigma}_b$. From $t = 2$ onwards, I simulate the economy 10,000 times for a total of 25 periods, and average across simulations. Variables are expressed in percentage from the no crises path, except default rates which are expressed in annual percentage points deviations.

6. Conclusion

This paper develops a new model of deposit insurance design that is able to capture key aspects of the current debate: failure of a small share of banks feeds back into performing banks and real economy activity, and deposit insurance coverage can be state-contingent. The model is calibrated to the US data and matches a series of facts regarding the probability, persistence and severity of fundamental and liquidity-driven banking crises.

I find that, under fast government reaction, the current US practice of increasing deposit insurance ex-post is optimal: it prevents liquidity crises and contains moral hazard. This result, however, breaks under slow government reaction. That is, state-contingent deposit insurance increases can mitigate the effects of liquidity crises, but not prevent them. Therefore, this implementation delay has crucial implications for DI design: increasing the ex-ante level of coverage is preferred than doing so ex-post. Contrary to the FDIC proposals, however, slow government reaction does not justify full fixed ex-ante deposit insurance. The optimal ex-ante level of deposit insurance stands at 65 % of total deposits, which is around 10 percentage points higher than the current limit, but substantially below full insurance.

The analysis presented in this paper comes with some important caveats. First, in my model, the level of deposit insurance coverage is expressed in share of insured deposits, but the real-life policy is expressed in dollars. This assumption simplifies the analysis by ensuring depositors are ex-post identical. However, as argued by Cooper and Kempf (2016) this assumption neglects important distributional consequences associated with deposit insurance. Second, evidence in Baron et al. (2021) suggests that liquidity-driven crises arise after equity declines, whereas in my model they occur due to exogenous changes in bank asset liquidity. Third, Cipriani et al. (2024) argue that during the 2023 banking turmoil, surviving banks who experienced deposit withdrawals paid back depositors by borrowing from other banks, rather than by fire-selling their assets. Addressing these limitations is left for future work.

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Online Appendix

A Partial Equilibrium

A.1 Equilibrium Definition

The aggregate profits of banks Π^b are given by the average returns of performing banks minus the repayment of depositors of performing banks, as illustrated by (1) below. Note that this equation accounts for the fact that, as proven in Proposition 1, depositors will always roll-over non-defaulting banks. The profits to the banks depend on the effective default threshold $\tilde{\omega}$, but not on which share of failing banks fail in the morning and in the afternoon.

$$\Pi^b = \int_{\tilde{\omega}}^{\infty} \omega R_k K_b dF(\omega) - \int_{\tilde{\omega}}^{\infty} R_d D_b dF(\omega) \tag{1}$$

The ex-post aggregate return on deposits, given by (2), is the sum of the returns on performing and non-performing debt. The first term states that households get the promised interest on performing banks. Note again that this term internalizes that households will not withdraw early from performing banks. The second term captures the ex-post return on debt held at failing banks, which in turn depends on the payment made by the DIA, denoted Θ^{DIA}, and the resources households get from early withdrawal of banks that fail in the morning, given by $\int_0^{\omega^*} \frac{\lambda\omega R^k}{1-\phi} dF(\omega)$ [19].

$$\Pi^d = \underbrace{\int_{\tilde{\omega}}^{\infty} dF(\omega) R^d D_b}_{\text{Performing}} + \underbrace{\Theta^{DIA} + D_b \int_0^{\omega^*} \frac{\lambda\omega R^k}{1-\phi} dF(\omega)}_{\text{Non-performing}} \tag{2}$$

The resources and payments made by the DIA crucially depend on the share of fundamental and panic driven default. Focus first on the assets recoverd by the DIA, denoted Π^{DIA} and given by (3). As argued in section 2.3, the DIA will recover no assets on banks that default in the morning. Therefore, when $\omega^* \geq \bar{\omega}$, all banks that fail do so in the morning (and through a panic) and the DIA recovers no assets. When $\omega^* < \bar{\omega}$, however, a share $F(\bar{\omega}) - F(\tilde{\omega})$ survives the morning but fails in the afternoon, so the DIA will recover a share λ of the assets of the banks that fail in the afternoon.

$$\Pi^{DIA} = \begin{cases} \int_{\omega^*}^{\bar{\omega}} \lambda\omega R^k K_b dF(\omega) & \text{if } \bar{\omega} \geq \omega^* \\ 0 & \text{if } \omega^* > \bar{\omega} \end{cases} \tag{3}$$

The payments made by the deposit insurance agency, denoted Θ^{DIA} and given by (4), also depend on both the panic and fundamental thresholds. I describe each case separately. First, when $\omega^* > \bar{\omega}$ all banks fail through a panic. The liabilities to the DIA are just the deposit insurance limit κ since it recovers no

[19] Note that for each failing bank $\omega < \omega^*$ that share of households paid before the bank runs out of resources is $p_m(\omega)$ given by equation (1), and therefore, to get aggregate value we integrate over $[0, \omega^*)$

assets, which must be paid to the depositors of all failing banks that did not receive early withdrawals. Second, when $\omega^* < \bar{\omega}$ a share $F(\bar{\omega}) - F(\omega^*)$ of banks fails in the afternoon and a share $F(\omega^*)$ fails in the morning. The payments of the DIA for the morning defaults are the same as when $\omega^* > \bar{\omega}$. In contrast, for the afternoon defaults the DIA pays at least the limit κ. One can find a threshold ω_k to be the minimum value of ω such that the DIA pays above the limit κ [20]. When $\omega_k \notin [\bar{\omega}, \omega^*]$ the always pays the limit κ. When $\omega_k \in [\bar{\omega}, \omega^*]$, the DIA pays the recovery value for any $\omega < \omega_k$ and the limit to for any $\omega > \omega_k$.

$$\Theta^{DIA} = \begin{cases} \left[\int_0^{\omega^*} 1 - \frac{\lambda\omega R^k}{1-\phi} dF(\omega)\right]\kappa D_b & \text{if } \omega^* > \bar{\omega} \\ \left[\int_0^{\omega^*} 1 - \frac{\lambda\omega R^k}{1-\phi} F(\omega) + \int_{\omega^*}^{\bar{\omega}} dF(\omega)\right]\kappa D_b & \text{if } \omega^* \leq \bar{\omega} \text{ and } \omega_k \notin [\omega^*, \bar{\omega}] \\ \left[\int_0^{\omega^*} 1 - \frac{\lambda\omega R^k}{1-\phi} F(\omega) + \int_{\omega^*}^{\bar{\omega}} dF(\omega)\right]\kappa D_b + \int_{\omega^*}^{\omega_\kappa} \frac{\lambda\omega}{\bar{\omega}} dF(\omega) D_b & \text{if } \omega^* \leq \bar{\omega} \text{ and } \omega_k \in [\omega^*, \bar{\omega}] \end{cases} \tag{4}$$

The DIA finances the difference between the recovered resources from defaulting banks, $\Pi^D IA$ and the payments made to depositors of such banks Θ^{DIA}, via lump-sum taxes T, as captured by

$$T = \Theta^{DIA} - \Pi^{DIA} \tag{5}$$

Definition 1 below contains a full description of the Partial Equilibrium of this economy. Even though the goods market clearing condition (10) holds, it constitutes a partial equilibrium in the sense that the deposit rate R^d does not reflect the expected pay-offs to the household are given by (2). This assumption will be relaxed in Section 3..

Definition 1. *Partial Equilibrium*

Given K_b, D_b, R^k, R^d, a Partial Equilibrium consists of allocations $C, \Pi^b, \Pi^d, \Pi^{DIA}, \Theta^{DIA}, T$ and default thresholds $\bar{\omega}, \omega^*, \tilde{\omega}$ such that (8),(10)-(14) hold, and ω^* solves the equation in 1.

A.2 Proposition 1

Let $\hat{\omega}_{h,b}$ be the signal received by agent h about the productivity of bank b. Agent h knows that the distribution of signals is $\hat{\omega} = \omega_b + \nu$, where ν is a noise term distributed $\nu \sim U(-\bar{\nu}, \bar{\nu})$. Therefore, h knows that signals received by other agents $\hat{\omega}_{-h,b}$ is bounded in the interval $[\hat{\omega}_{h,b} - \bar{\nu}, \hat{\omega}_{h,b} + \bar{\nu}]$. Assume further that agent h receives a signal ω^* such that she is indifferent between W and R. Then, the agent knows that any agent receiving $\omega_{-h,b} < \omega^*$ will choose W and any agent receiving $\omega_{-h,b} > \omega^*$ will choose R. Denoting $p_{-h}(\hat{\omega_{h,b}})$ to be the the share of agents that depositor h thinks will choose W, given signal $\hat{\omega}_{h,b}$ follows

$$p_{-h}(\hat{\omega}_{h,b}) = \begin{cases} 1 & \text{if } \hat{\omega}_{-h,b} < \omega_{h,b} - \bar{\nu} \\ \frac{1}{2} + \frac{\omega^* - \omega_{-h,b}}{2\bar{\nu}} & \text{if } \hat{\omega}_{-h,b} \in [\omega_{h,b} - \bar{\nu}, \omega_{h,b} - \bar{\nu}] \\ 0 & \text{if } \hat{\omega}_{-h,b} > \omega_{h,b} + \bar{\nu} \end{cases} \tag{A.2.1}$$

[20] To derive this impose $p_k = 1$ in equation (7), substitute in for $p_m(\omega)$ using equation (1), and solve for ω

Therefore, the posterior beliefs of the agent $p_{-h}(\hat{\omega}_{h,b}) \sim U(0,1)$. Since $\omega_{h,b} = \omega^*$, and an agent with signal ω^* is indifferent between W and R. Then by taking the limit where $\bar{\nu} \to 0$, and expectations of the net pay-off function of Table 1, the indifference condition writes

$$\int_0^{p_a(\omega^*)} (1-\epsilon)R^D dp + \int_{p_a(\omega^*)}^{p_k(\omega^*)} \Big[\frac{1}{1-p}(\frac{\hat{\omega}^*}{\bar{\omega}} - \frac{p\epsilon}{\lambda}) - \epsilon R^D\Big] dp + \int_{p_k(\omega^*)}^{p_a(\omega^*)} (\kappa-\epsilon)R^D dp + \int_{p_m(\omega^*)}^{1} \frac{\kappa+\epsilon}{p} R^D dp = 0 \tag{A.2.2}$$

After integrating and some algebra we can rewrite the indifference condition as

$$p_m(\omega^*)\Omega_1 + \Omega_2 + Ln(p_m(\omega^*))(1+\kappa R^d) = 0 \tag{A.2.3}$$

where Ω_1 and Ω_2 are given by

$$\Omega_1 = \epsilon\frac{R^d - 1}{\epsilon - \lambda} - \frac{\kappa R^d}{1-\kappa R^d} + \kappa R^d + Ln(\frac{\lambda - \epsilon}{1-\kappa R^d}) \tag{A.2.4}$$

$$\Omega_2 = -\frac{\lambda(R^d-1)}{1-\lambda} + \frac{(\kappa R^d)^2}{1-\kappa R^d}) - Ln(1-\kappa R^d) \tag{A.2.5}$$

So far we have found a threshold ω^* such that a household h is indifferent between W and R. Let $u(j,p,\omega)$ be the pay-off to h with beliefs p and signal ω, from strategy $j \in \{W,R\}$, and $u(p,\omega) = u(R,p,\omega) - u(W,p,\omega)$. For ω^* to constitute a unique equilibrium of the global game, we need the following conditions need to hold (see Goldstein and Pauzner (2005), De Groot (2021)):

1. **State Monotonicity**: $\forall p$, pay-off $u(p,\omega) = u(R,p,\omega) - u(W,p,\omega)$ must be non-decreasing in ω

2. **Action Single Crossing**: $\forall \omega \in \mathbb{R}$, $\exists\ p^* \in \mathbb{R}$

   - $u(p,\omega) > 0$ if $p < p^*$
   - $u(p,\omega) < 0$ if $p > p^*$
   - p^* is unique

3. **Uniform Limit dominance** $\exists\ \omega_L \in \mathbb{R}, \omega_H \in \mathbb{R}$ and $\mu \in \mathbb{R}_{++}$ s.t. $\forall p \in (0,1]$

   - $u(p,\omega^H) > \mu$
   - $u(p,\omega^L) < \mu$

4. **Monotone Likelihood**: if $\bar{x} - \underline{x} > 0$, $\frac{h(\bar{x}-\omega)}{h(\underline{X}-\omega)}$ is increasing in ω, where $h(\cdot)$ is distribution of noise.

5. **Continuity**: $\int_0^p g(p)u(p,\omega)$ is continious w.r.t to $g(\cdot)$ and signal.

6. **Strict Laplacian state Monotonicity**: $\exists! \hat{\omega}^*$ solving $\int_0^1 u(p,\hat{\omega}^*)dp = 0$.

Conditions 1., 2., and 3. have already been discussed in the main text. Condition 4. is a technical condition that follows from the assumption that the noise of the signal is uniformly distributed. Condition 5. refers to continuity with respect to the weak topology. As argued by Morris and Shin (2003), this condition holds for discontinuity in pay-offs like the one that at $p_m(\omega)$ in this model. Condition 6. requires that there is a unique solution to equation A.1.3. I have no tverified this condition, but so far all calibrations I tried gave me a unique solution to it.

A.3 Proposition 2

We first find $\bar{W}$, which is the welfare of the economy with $\omega^* = 0$. Throughout, I use the upper bar notation to denote that the flows of resources correspond to those of the economy without coordination failure. From (11) and (12) it follows that

$$\bar{\Pi}^d + \bar{\Pi}^b - \bar{\Theta}^{DIA} = \int_{\bar{\omega}}^{\infty} \omega R^k K dF(\omega) \tag{A.3.1}$$

From (15) it follows that

$$\bar{\Pi}^{DIA} - T = -\bar{\Theta}^{DIA} \tag{A.3.2}$$

Substituting into (A.2.1) results in

$$\bar{\Pi}^d + \bar{\Pi}^b + \bar{\Pi}^{DIA} - T = \int_{\bar{\omega}}^{\infty} \omega R^k K dF(\omega) \tag{A.3.3}$$

Re-arranging (A.2.3), and using the goods market clearing condition, it follows that

$$\bar{C} = \bar{\Pi}^d + \bar{\Pi}^b - T = \int_{\bar{\omega}}^{\infty} \omega R^k K dF(\omega) + \bar{\Pi}^{DIA} \tag{A.3.4}$$

Finally, using (13), we get that

$$\bar{C} = \int_{\bar{\omega}}^{\infty} \omega R^k K_b dF(\omega) + \int_{0}^{\bar{\omega}} \omega \lambda R^k K_b dF(\omega) \tag{A.3.5}$$

and therefore $\bar{W} = v(\bar{C})$ where $v(C)$ is the utility function and is assumed to be increasing C.

Applying the same steps for the economy with $\omega^* > 0$ one can show that

$$C^* = \int_{\tilde{\omega}}^{\infty} \omega R^k K_b dF(\omega) + \int_{0}^{\tilde{\omega}} \omega \lambda R^k K_b dF(\omega) \tag{A.3.6}$$

Consider now the case where $\omega^* \leq \bar{\omega}$. Then, it follows that

$$C^* = \int_{\bar{\omega}}^{\infty} \omega R^k K_b dF(\omega) + \int_{0}^{\bar{\omega}} \omega \lambda R^k K_b dF(\omega) \tag{A.3.7}$$

which implies that $\bar{W} = W^*$. In contrast, when $\omega^* > \bar{\omega}$ it follows that

$$C^* = \int_{\omega^*}^{\infty} \omega R^k K_b dF(\omega) + \int_0^{\omega^*} \omega\lambda R^k K_b dF(\omega) \tag{A.3.8}$$

using the fact $\omega^* > \bar{\omega}$, we can rewrite C^* as

$$C^* = \int_{\bar{\omega}}^{\infty} \omega R^k K_b dF(\omega) - \int_{\bar{\omega}}^{\omega^*} \omega R^k K_b dF(\omega) + \int_0^{\bar{\omega}} \omega\lambda R^k K_b dF(\omega) + \int_{\bar{\omega}}^{\omega^*} \omega\lambda R^k K_b dF(\omega) = \bar{C} - \int_{\omega^*}^{\bar{\omega}} (1-\lambda)\omega R^k K dF(\omega \tag{A.3.9}$$

Therefore $v(C^*) < v(\bar{C})$ which implies $W^* < \bar{W}$.

A.4 Proposition 3

Assuming $\epsilon = 1/R^d$, we can rewrite (A.1.3.) as

$$F(\omega^*) = p_m(\omega^*)\Omega_1 + \Omega_2 + log(p_m(\omega^*))(1 - \kappa R^d) = 0 \tag{A.4.1}$$

where

$$p_m(\omega^*) = \frac{\lambda\omega^* R^d}{\bar{\omega}} \tag{A.4.2}$$

and

$$\bar{\omega} = \frac{R^d D_b}{R^k K_b} = \frac{R^d}{R^k}(1 - \phi) \tag{A.4.3}$$

and

$$\Omega_1 = \underbrace{\frac{R^d - 1}{1 - \lambda R^d}}_{\Omega_{11}} + \underbrace{\frac{(\kappa R^d)^2}{1 - \kappa R^d}}_{\Omega_{12}} + \underbrace{log(\frac{1 - \kappa R^d}{1 - \lambda R^d})}_{\Omega_{13}} \tag{A.4.4}$$

$$\Omega_2 = \underbrace{\frac{\lambda(1 - R^d)}{1 - \lambda}}_{\Omega_{21}} + \underbrace{\frac{(\kappa R^d)^2}{1 - \kappa R^d}}_{\Omega_{22}} - \underbrace{log(1 - \kappa R^d)}_{\Omega_{23}} \tag{A.4.5}$$

Totally differentiating (A.3.1) and re-arranging we have that

$$\frac{\partial\omega^*}{\partial\kappa} = -\frac{\partial F}{\partial\kappa} \cdot \left(\frac{\partial F}{\partial\omega^*}\right)^{-1} \tag{A.4.6}$$

Step 1: deriving $\frac{\partial F}{\partial\kappa} < 0$.

Step 2 deriving $\frac{\partial F}{\partial\omega^*} < 0$.

Step 3 Put everything together

Since $\frac{\partial F}{\partial\omega^*} < 0$ and $\frac{\partial F}{\partial\kappa} < 0$, it follows from A.4.1, that $\frac{\partial\omega^*}{\partial\kappa} < 0$.

A.5 Proposition 4

From Proposition 2 it follows that κ^* must be such that $\bar{\omega} = \omega^*$. Substituting $\bar{\omega}$ into $p_m(\omega^*)$ given by (1) it follows that

$$p_m = \lambda R^d \tag{A.5.1}$$

Substituting A.5.1 into A.4.1, and taking total derivatives, one can show that

$$\frac{\partial \kappa^*}{\partial \lambda} < 0 \tag{A.5.2}$$

B Dynamic General Equilibrium

B.1 Household Optimality Conditions

Let $\Lambda_{h,t+1} = \beta \frac{U_c(C_{t+1})}{U_c(C_t)}$ be the stochastic discount factor of the dynasty. The first order-conditions for capital and deposits are (B.1.1) and (B.1.2), respectively.

$$1 = \mathbb{E}_t\{\Lambda_{h,t+1}\tilde{R}_{d,t+1}\} \tag{B.1.1}$$

$$1 + \psi K_{h,t+1} = \mathbb{E}_t\{\Lambda_{h,t+1}R_{k,t+1}\} \tag{B.1.2}$$

B.2 Liquidity Default Threshold

The liquidity default threshold is determined in the same way as in the static model. However, all the elements in the equation are time-varying and determined in general equilibrium. The equation is given by

$$p_{m,t}(\omega_t^*)\Omega_{1,t} + \Omega_{2,t} + log(p_{m,t}(\omega_t^*))(1 - \kappa_t R_{d,t}) = 0 \tag{B.2.1}$$

where

$$p_{m,t}(\omega_t^*) = \frac{\lambda_t \omega_t^* R_{d,t}}{\bar{\omega}_t}$$

$$\Omega_{1,t} = \underbrace{\frac{R_{d,t} - 1}{1 - \lambda_t R_{d,t}}}_{\Omega_{11,t}} + \underbrace{\frac{(\kappa_t R_{d,t})^2}{1 - \kappa_t R_{d,t}}}_{\Omega_{12,t}} + \underbrace{log(\frac{1 - \kappa_t R_{d,t}}{1 - \lambda_t R_{d,t}})}_{\Omega_{13,t}}$$

$$\Omega_{2,t} = \underbrace{\frac{\lambda(1 - R_{d,t})}{1 - \lambda_t}}_{\Omega_{21,t}} + \underbrace{\frac{(\kappa_t R_{d,t})^2}{1 - \kappa_t R_{d,t}}}_{\Omega_{22,t}} - \underbrace{log(1 - \kappa_t R_{d,t})}_{\Omega_{23,t}}$$

B.3 Optimal Risk-Management Effort

The future profits $\mathbb{E}_t R_{E,t+1}$ given by equation (B.3.1). Bankers choose $e_{b,t}$ in order to maximize their expected future profits internalizing ex-ante the following aspects. First, the direct costs of risk-management effort in their ex-post returns. Second, the expected future default outcomes of individual banks. Third, the effect of interest rate on deposits on ex-post profits.

$$\mathbb{E}_t R_{E,t+1} = \mathbb{E}_t \Big\{ \Lambda_{b,t+1} [\underbrace{H(\tilde{\omega}) - F(\tilde{\omega}) R_{d,t}(1-\phi)}_{\Pi_{t+1}} - g(e_{b,t})] \frac{R_{k,t+1}}{\phi} \Big\} \tag{B.3.1}$$

The first effect through operating costs is the first-order derivative of the cost function with respect to effort

$$\frac{\partial g(e_{b,t})}{\partial e_{b,t}} = 1 \tag{B.3.2}$$

The second direct effect of defaults on future profits can be found applying the chain rule as follows

$$\frac{\partial \Pi_{t+1}}{\partial e_{b,t}} = \frac{\partial \Pi_{t+1}}{\partial \sigma} \frac{\partial \sigma}{\partial e_{b,t}} = \frac{\partial H(\omega)}{\partial \sigma} \frac{\partial \sigma}{\partial e_{b,t}} - \frac{\partial F(\omega)}{\partial \sigma} \frac{\partial \sigma}{\partial e_{b,t}} R_{d,t}(1-\phi)$$

Note that from (23) it follows that $\frac{\partial \sigma}{\partial e_{b,t}} = 1$ so we can simplify the above expression as

$$\frac{\partial \Pi_{t+1}}{\partial e_{b,t}} = \frac{\partial H(\tilde{\omega})}{\partial \sigma} - \frac{\partial F(\tilde{\omega})}{\partial \sigma} R_{d,t}(1-\phi) \tag{B.3.3}$$

The third effect is the indirect effect of deposit rates on profits and is given by (B.3.4) where the first term captures the reduction in profits of non-defaulting banks and the second term captures the effect of interest rates on the default threshold.

$$\frac{\partial \Pi_{t+1}}{\partial R_{d,t}} = \frac{\partial H(\tilde{\omega}_{t+1})}{\partial \tilde{\omega}_{t+1}} \frac{\partial \tilde{\omega}_{t+1}}{\partial R_{d,t}} - \frac{\partial F(\tilde{\omega}_{t+1})}{\partial \tilde{\omega}_{t+1}} \frac{\partial \tilde{\omega}_{t+1}}{\partial R_{d,t}} (1-\phi) R_{d,t} + F(\tilde{\omega}_{t+1})(1-\phi) \tag{B.3.4}$$

Note that, depending on the state of the economy the effective default threshold $\tilde{\omega}_{t+1}$ is either the fundamental threshold $\bar{\omega}_{t+1}$ or the liquidity threshold ω^*_{t+1}. Therefore, the effect of interest rates on the effective default threshold $\tilde{\omega}_{t+1}$ is

$$\frac{\partial \tilde{\omega}_{t+1}}{\partial R_{d,t}} = \begin{cases} \frac{\partial \omega^*_{t+1}}{\partial R_{d,t}} & \text{if } \omega^*_t > \bar{\omega}_t \\ \frac{\partial \bar{\omega}_{t+1}}{\partial R_{d,t}} & \text{if } \omega^*_t \leq \bar{\omega}_t \end{cases} \tag{B.3.5}$$

From (B.1.2) and (B.5.3) it follows that the required interest rate on bank deposits depends on the banks default rate and consequently on banks risk and risk-management choice. For simplicity, I assume that banks approximate the deposit rate following

$$1 = R_{d,t} \mathbb{E}_t \Big\{ \Lambda_{t+1} \Big[F(\tilde{\omega}_{t+1}) + [1-\kappa_{t+1}][1 - F(\tilde{\omega}_{t+1})] \Big] \Big\} \tag{B.3.6}$$

which states that the required interest rate must account for the payments made by defaulting banks and the payments made by the DIA for defaulting banks[21]. Re-arranging (B.3.7) and taking partial derivatives one can show that banks' beliefs about the effect of their risk-management effort on the required interest rate follow

$$\frac{\partial R_{d,t}}{\partial e_{b,t}} = \mathbb{E}_t\Big\{\Lambda_{t+1}\Big[F(\tilde{\omega}_{t+1}) + [1-\kappa_{t+1}][1-F(\tilde{\omega}_{t+1})]\Big]\Big\} \tag{B.3.7}$$

B.4 Deposit Insurance Agency

As argued in Section 2., the DIA recovers no assets from banks that default in the morning. Therefore, the resources of the DIA at time t, denoted Π_t^{DIA} are

$$\Pi_t^{DIA} = \begin{cases} [H(\bar{\omega}) - H(\omega^*)]\lambda_t R_{k,t} K_{b,t} & \text{if} \quad \omega_t^* \leq \bar{\omega}_t \\ 0 & \text{if} \quad \omega_t^* > \bar{\omega}_t \end{cases} \tag{B.4.1}$$

This equation states that whenever all banks default in the morning ($\omega_t^* > \bar{\omega}$), the DIA recovers no resources. In contrast, whenever some banks default in the afternoon ($\omega_t^* \leq \bar{\omega}$), it recovers a fraction λ_t of the assets of the banks that survived the morning, but failed in the afternoon.

The DIA must pay at least a fraction κ of the depositors of failed banks who did not get paid by the banks. When all defaulting banks fail in the morning ($\omega_t^* > \bar{\omega}_t$), the DIA pays Θ_t^m. This term captures that a share of depositors are "early" in the queue and get paid by the banks and the remainder of depositors are covered by DIA[22]. Whenever some banks survive the the morning but fail in the afternoon ($\omega_t^* < \bar{\omega_t}$), there are two possible outcomes: either the DIA pays the limit κ to the depositors of all banks, or it pays more than the limit κ for some banks. The former occurs when for all banks that default in the afternoon, the DIA recovery value per depositor is less than the limit κ. This happens when $\omega_{\kappa,t} \geq \bar{\omega}_t$ [23], with payments denoted by $\Theta_t^{\kappa^-}$. In contrast, if $\omega_{\kappa,t} < \bar{\omega}_t$, all the banks that fail in the afternoon and satisfy $\omega \in [\omega_{k,t}, \bar{\omega}]$, will have recovery values larger than the limit κ. For these banks, the DIA pays the recovery value per

[21]This presents a simplification in the sense that the payments from defaulting banks are given by (B.5.3), which is slightly more involved

[22]This share is give by $p^*(\omega)$ and the remainder $1 - p^*(\omega)$ will get paid by the DIA. One can show that $p^*(\omega) = \omega\lambda_{t+1}\bar{\omega}_{t+1}R_t^d$. Given ω a bank fails in the morning if $\lambda_{t+1}R_{t+1}^k K_{b,t+1} = pD_{b,t+1}$

[23]Note that $\omega_{t+1}^\kappa = \frac{\kappa}{\lambda_{t+1}\bar{\omega}_{t+1}}$. To derive this, note that the recovery value per depositor is given $RV_{t+1}(\omega)\lambda_{t+1}\frac{\omega R_{t+1}^k K_{b,t+1}}{R_t^d D_{b,t+1}}$. Setting $RV_{t+1}(\omega) = \kappa$, and solving for ω yields ω_{t+1}^κ

depositor which is given by $\Theta_t^{\kappa^+}$. These cases are captured by Θ_t^{DIA} and given by

$$\Theta_t^{DIA} = \begin{cases} \underbrace{\left[F(\omega^*) - H(\omega^*)\frac{\lambda_t R_{k,t}}{1-\phi}\right]\kappa D_{b,t}}_{\equiv \Theta_t^m \text{ (morning default)}} & \text{if } \omega_t^* > \bar{\omega}_t \\ \underbrace{\left[\ F(\bar{\omega}) \quad - \quad F(\omega^*)\ \right]\kappa D_{b,t}}_{\equiv \Theta_t^{\kappa^-} \text{ (DI limit)}} \ + \ \Theta_t^m & \text{if } \omega_t^* \leq \bar{\omega}_t \ \ \& \ \ \omega_{k,t} \notin [\omega_t^*, \bar{\omega}_t] \\ \underbrace{\left[\ H(\omega_{\kappa,t}) \quad - \quad H(\omega_t^*)\ \right]\frac{\lambda_t}{\bar{\omega}} D_{b,t}}_{\equiv \Theta_t^{\kappa^+} \text{ (over DI limit)}} \ + \ \Theta_t^{\kappa^-} \ + \ \Theta_t^m & \text{if } \omega_t^* \leq \bar{\omega}_t \ \ \& \ \ \omega_{k,t} \in [\omega_t^*, \bar{\omega}_t] \end{cases} \tag{B.4.2}$$

Finally, the DIA finances the differences between inflows and outflows via lump-sum taxes on households

$$T_t = \Theta_t^{DIA} - \Pi_t^{DIA} \tag{B.4.3}$$

B.5 Return on deposits

Households' realized return on deposits $\tilde{R}_{d,t}$ depends on the pay-off on performing debt, given by $(1 - F(\tilde{\omega}))R_{d,t}$ and the pay-off on defaulting debt. The pay-off from the banks that fail in the morning denoted $R_{d,t}^m$ are defined by (B.5.1) and correspond to the DIA payments net of early withdrawals. The pay-off from banks that default in the afternoon, denoted $\tilde{R}_{d,t}^a$ are given by (B.5.2) and contain only payments made by the DIA, both for banks with recovery values above and below the limit κ.

$$\tilde{R}_{d,t}^m = F(\omega_t^*)\kappa + [1-\kappa]H(\omega_{t+1}^*)\lambda_t\bar{\omega}_t R_{d,t-1} \tag{B.5.1}$$

$$\tilde{R}_{d,t}^a = R^d\kappa[F(\omega_t^\kappa) - F(\bar{\omega}_t)] + R_{d,t-1}[G(\bar{\omega}_{t+1}) - G(\omega_{t+1}^\kappa)]\lambda_{t+1}\bar{\omega}_{t+1} \tag{B.5.2}$$

The total realized return per unit of household deposits $\tilde{R}_{d,t}$ therefore writes

$$\tilde{R}_{d,t} = \begin{cases} [1 - F(\omega_t^*)]R_{d,t-1} \ + \ \tilde{R}_{d,t}^m & \text{if } \omega_t^* > \bar{\omega}_t \\ [1 - F(\bar{\omega}_t)]R_{d,t-1} \ + \ \tilde{R}_{d,t}^m \ + \ \tilde{R}_{d,t}^a & \text{if } \omega_t^* \leq \bar{\omega}_t \end{cases} \tag{B.5.3}$$

Note that the required interest rate $R_{d,t}$ must adjust in equilibrium to satisfy the realized return equation (B.5.3) as well as the optimality condition of households with respect to deposits (B.1.2).

B.6 Market Clearing

The total stock of capital in the economy is given by

$$K_t = K_{b,t} + K_{h,t} \tag{B.6.1}$$

Market clearing condition for deposits is

$$D_{h,t} = D_{b,t} \tag{B.6.2}$$

and for labour is

$$L_t = 1 \tag{B.6.3}$$

B.7 Equilibrium Definition

I now define the equilibrium. Given initial conditions $[K_{b,0}, K_{h,0}, e_0, R_{d,0}, \lambda_0, \sigma_0]$ a sequential competitive equilibrium consists of sequences of

- Prices $\{r_{k,t}, w_t, R_{d,t}\}_{t=0}^{\infty}$
- Returns$\{R_{k,t}, \tilde{R}_{d,t}, R_{E,t}\}_{t=0}^{\infty}$
- Production inputs $\{K_t, L_t\}_{t=0}^{\infty}$
- Households' plans $\{D_{h,t+1}, K_{h,t+1}, C_t\}_{t=0}^{\infty}$
- Banks' choices $\{K_{b,t+1}, D_{b,t+1}\}_{t=0}^{\infty}$ and default thresholds $\{\tilde{\omega}_t, \bar{\omega}_t, \omega_t^*, \}_{t=0}^{\infty}$
- Bankers' choices $\{div_{b,t}, E_{b,t}, e_{b,t}\}_{t=0}^{\infty}$, value of equity $\{v_{b,t}\}_{t=0}^{\infty}$, net-worth $\{N_{b,t}\}_{t=0}^{\infty}$, and profits $\{\Pi_t\}_{t=0}^{\infty}$
- DIA actions: $\{\kappa_t, \Theta_t^{DIA}, \Pi_t^{DIA}, T_t\}_{t=0}^{\infty}$
- Realizations of the exogenous shocks $\{\lambda_t, \bar{\sigma}_t\}_{t=0}^{\infty}$ and bank risk $\{\sigma_t\}_{t=0}^{\infty}$

such that, for all t, the following conditions hold:

- Producers optimality conditions (12) and (13)
- Household optimality conditions (B.1.1)-(B.1.2), and (14)
- Banks' optimality conditions (17)-(18)
- Banks' liquidity default threshold (B.2.1), fundamental threshold

  $$\bar{\omega}_t = \frac{R_{d,t}}{R_{k,t}}(1-\phi)$$

  and effective default threshold $\tilde{\omega}_t$

  $$\tilde{\omega}_t = \text{Max}\{\bar{\omega}_t, \omega_t^*\}$$

- Individual bankers' optimality conditions for effort (B.3.7) and

  $$div_{b,t} = 0$$

  $$E_{b,t} = N_{b,t}$$

- Aggregate bankers' value of equity (28), law of motion of net-worth (29), and profits (30)

- DIA flows equations (B.4.1)-(B.4.3) and policy

$$\kappa_t = f(\lambda_t, \bar{\sigma}_t)$$

- Returns on deposits (B.5.3), capital

$$R_{k,t} = r_{k,t} + (1 - \delta)$$

  and equity

$$R_{E,t} = [H(\tilde{\omega}_t) - F(\tilde{\omega}_t)\bar{\omega}_t - e_{b,t}^2]\phi R_{k,t+1}$$

- Market clearing conditions (B.6.1)-(B.6.3)
- Exogenous shocks processes (31) - (32)
- Realized bank risk (22).

C Data Appendix

The target moments for the model calibration are computed as follows.

Return on Equity. I collect data on bank equity returns from FRED. In particular, I download equity return series for all US banks for the period 1984-2020. The average return over the sample period is 11.14%.

Deposit Insurance. I use FDIC data on the average share of uninsured domestic deposits of US commercial banks from 1970 to 2022. Specifically, I download the underlying data for the report on deposit insurance reform FDIC (2023). The 2008 value stands at 36.7%, corresponding to a level of deposit insurance that covers 67.3% of total deposits. The long-run average stands at 69.91 %.

Bank Default. I construct a series of asset-weighted bank default using FDIC data as follows. First, I collect data on the asset value of each individual commercial bank that failed over the period 1970-2022. Second, I obtain yearly data on the total value of US commercial banks from 1970 to 2022. Third, I compute asset-weighted bank default rate by dividing the total asset value of all failed banks during each year, over the value of all the commercial banks.

Crises Classification. The methodology developed by Baron et al. (2021) classifies the following years as banking crises: 1974, 1984, 1990, and 2008. They classify the 1974 to be a silent crises (equity declines without bank defaults), the 1984 and 2008 as default crises with panics, and the 1990 crises as a default crises without panics. However, the FDIC default data does not align very closely with this classification.

In particular, the bank default series shows that often times, the bank default rates start increasing prior the crises year identified by Baron et al. (2021).

To overcome this challenge, I classify as a crises year all observations with bank default rates above the long-run average. This delivers the following observations as crises years: 1982, 1984, 1988, 1989, 1990, 1991, 1992, 2008, 2009, 2010. I then allocate this years to fundamental crises based on the classification of Baron et al. (2021). The fundamental crises years are then 1982, 1988 , 1989, 1990, 1991 and 1992. The liquidity default years are 1984, 2008, 2009, and 2010.

Crises Moments. On the basis of the crises classification and the default rates data, I compute a series of moments. For fundamental crises, I get an average default rate of 1.89 %, an unconditional probability of 11.32 %, and a probability of transitioning to a fundamental crises years of 4.55 %. For liquidity crises, I get an average default rate of 4.52 %, an unconditional probability of 7.52 %, and a probability of transitioning to a liquidity crises years of 4.55 %.