Bailouts, Bank Regulation and Risk-Taking: A General-Equilibrium Exposition*

Luigi Falasconi†

Job Market Paper

Abstract

This paper provides a unified account of the role of bailout expectations and regulation in shaping the dynamics of banks' credit spreads and risk-taking incentives. I document that market-implied losses given default increased substantially following the Great Financial Crisis, became more volatile, and became more correlated with economy-wide and bank-specific fundamentals, reflecting diminished bailout expectations. Using a dynamic general equilibrium of financial intermediation featuring default risk and time-varying bailout expectations, I show that lower bailout expectations substantially raised credit spreads at the onset of the crisis and that their importance diminished thereafter. Banks endogenous deleveraging, together with higher capital requirements, explain around half of the recovery in credit spreads post-crisis. These findings help explain how reduced bailout expectations and tighter regulation, by raising banks' cost of capital, have moved the banking sector away from risky asset markets.

*I am indebted to William Diamond, Alessandro Dovis, Urban Jermann and Enrique Mendoza for valuable advice. I want to thank Giovanni Bonfanti, Harold Cole, Vadim Elenev, Tim Landvoigt, Quinn Maingi, Caterina Mendicino, Lukas Nord, Guillermo Ordonez, Gianmarco Ruzzier, Alex Sawyer, Dominik Supera, Chi Xu for their useful comments.

†Department of Economics, University of Pennsylvania. Email: luigif@sas.upenn.edu.

1 Introduction

Since the Global Financial Crisis, credit-default-swap (CDS) spreads on unsecured bank debt have more than tripled and have remained far above pre-crisis norms, signalling that markets now attach a much higher price to the possibility of bank default. Three explanations appear plausible: first, banks may have shifted into business lines that enlarge tail exposures even while reported capital ratios improve; second, post-crisis regulation—Basel III surcharges, liquidity and funding ratios, and bail-inable total loss-absorbing capacity—may have raised the contractual loss that a CDS must insure and so boosted the spread independently of default risk; third, and in sharp contrast, investors may have revised downward the likelihood that governments will rescue wholesale creditors, so a given shock translates into larger creditor losses (Berndt et al. 2022); the puzzle is that standard balance-sheet indicators such as Tier 1 capital, leverage multiples, and non-performing loan shares all point to safer banks and therefore to lower, not higher, spreads; understanding whether today's premia reflect genuine fundamental risk or the evaporation of an implicit safety net is central to capital regulation, because if spreads are artificially low when bailouts are expected the optimal equity buffer must rise to neutralise risk-taking incentives, whereas if spreads already price fundamentals a further buffer may be unnecessary (Kareken & Wallace 1978, Chari & Kehoe 2016).

The first contribution of my paper is on measuring the risk-neutral losses given defaut for debt holders by exploiting the pricing of default risk in both credit and equity markets. To do this, I develop a valuation framework that compares how each claim (debt vs. equity) behaves in default states. If debt holders may be protected by a bailout while equity holders are fully wiped out upon default, then the left-tail risk for debt should be systematically smaller than that for equity. This reflects the market's perception of a possible government intervention. I then develop a simple method to recover the risk-neutral loss given default (LGD) by combining CDS and equity option contracts. Under a general class of stock price dynamics, deep out of the moneyAmerican put options replicate the risk-neutral probability of default (Carr & Wu 2011). I document how expected losses vary over time and respond to market conditions. The recovery of the mid-2000s sees projected creditor losses near ten percent, but these losses swell to around forty percent on the eve of the 2007–09 crisis and remain elevated through the downturn. As sovereign concerns spike in 2011, expected losses climb again before settling near twenty percent through much of the 2010s and then easing back toward ten percent by 2020. These countercyclical swings in market-implied losses mirror business-cycle stresses and confirm that creditors' downside exposure is far from constant. I also show that a significant portion (around 40%) of the variation in short-term credit spreads can be attributed to changes in risk-neutral losses given defaut.

I then ask whether these variations reflect true balance-sheet risk, bailout perceptions or simply shifts in market liquidity. To address this, I regress changes in expected losses on a suite of liquidity indicators—bid-ask spreads, trading volume, and open interest in out-of-the-money options, depth in CDS markets, plus aggregate measures like the TED–SOFR spread and the VIX—and isolate the component of loss movements driven by illiquidity. I construct a liquidity-adjusted expected-loss series by accumulating the residuals of this regression. Before the financial crisis, the original and liquidity-adjusted series move in lockstep, but as markets seize up in 2008–09, the adjusted losses rise significantly more. This finding implies that movements in expected losses post Great Financial Crisis reflect relatively more market condition signaling a lower likelihood of a bailout. However, the post crisis regime was also characterized by tighter regulation, which should have increased the cost of capital for banks, reduced risk-taking and therefore depressedthe credit spreads. In order to discipline the effect of tigheter regulation on credit spreads and isolate the role of bailout expectations, I develop a novel identification strategy to distinguish the two forces. The key insight is that the two move credit spreads and equity tail risk in opposite directions. When investors mark down the likelihood of a rescue, spreads rise—creditors expect bigger losses—while equity tail-volatility falls, because a larger share of downside is already borne by shareholders and the government put is weaker. Tighter loss-absorbing regulation (Basel III capital surcharges, TLAC, and single-point-of-entry resolution) works the other way for credit spreads: by forcing bondholders to share losses ex ante it flattens spreads, yet it reduces downside volatility for equity, whose residual claim becomes less levered and the upside potential for shareholders is reduced too. I exploit this sign reversal by examining the fixed-effect partial correlation between daily CDS spreads and the log model-free risk-neutral variance (SVIX) of equity returns. The slope jumps from 0.27 before 2008 to 0.37 after 2010—a one-third increase. Because lower bailout odds would have pushed the correlation down (spreads up, volatility down), the observed upward break cleanly identifies—and quantitatively pins down—the dominant role of the post-crisis regulatory regime. In effect, a one-standard-deviation bump in equity tail risk now elicits about a 35 percent larger proportional change in CDS premia than it did pre-Basel III, confirming that Dodd-Frank have sharpened rather than supplanted market discipline.

In the second part of the paper I build a dynamic general equilibrium model that embeds time varying bailout regimes. Banks hold portfolios of risky long-term bonds subject to mean reverting aggregate shocks and disasters. Bank fund those assets by issuing insured deposits which trade below market rates, uninsured bank bonds and and equity. When a bailout is granted the Treasury pays the full shortfall for bond-holders, otherwise bond investors recover the fraction of post-default asset value. My measurement strategy consists of combining the model with my estimated default probabilities and CDS spreads of the US banks to infer the component of credit spreads movements that is due to bailout expectations. I do so by applying the particle filter to the model and extracting the sequence of structural shocks that accounts for the behavior of credit spreads and risk-neutral default probabilities before, during and after the Great Financial Crisis. The estimated bailout probability allows a decomposition of observed credit spreads into a fundamental, a bailout and a regulation component. I rerun the exercise while holding bailout probabilities fixed at its pre-crisis level yet feeding in the same sequence of fundamental shocks; the resulting counterfactual spread isolates what investors would have demanded had bailout beliefs not moved. The difference between actual and counterfactual premia measures the time-varying bailout component. I show that diminished bailout odds explain more then half of the 2007–2009 surge in one-year spreads and about forty percent of their post-2010 plateau, with the remainder accounted for by asset risk and regulation.

To isolate the importance of endogenous leverage choice, I simulate a counterfactual in which banks are forbidden from adjusting uninsured bond issuance, holding it fixed at its ergodic mean. In this counterfactual, the one-year credit spread exceeds the baseline spread by roughly 80 basis points at the crisis peak—about one third larger than the 160 bp widening in the calibrated model. This gap measures the strength of the feedback channel through which higher uninsured funding costs lead banks to shrink debt and so mitigate part of the direct bailout-induced repricing. Ignoring this feedback would therefore understate the implied subsidy from government back-stops.

Building on this exercise, I then use the model to isolate how the post-crisis collapse in expected government support and tighter regulation reshaped both funding costs and banks' risk exposures. The anticipation of future bailouts of bondholders and other creditors always benefits shareholders ex ante and incentives risk-taking (Kareken & Wallace 1978). The average unsecured one-year spread paid by large U.S. banks jumps 34 basis points between the pre-2008 and the post-2010 periods. In a counterfactual that holds the pre-crisis bailout probability at its high level, the same spread rises by only 8.8 basis points. The remaining 25.5 bp—almost three-quarters of the observed increase—is therefore a pure bailout premium that investors demand once they expect to bear losses. Balance-sheet choices respond in kind. I build an asset-return factor from the model's loan-portfolio payoff and estimate its equity loading. The loading climbs 29 percent in the data-consistent baseline but edges down by 4 percent in the high bailout probability counterfactual, implying a 33-percentage-point swing in exposure that is fully attributable to weaker bailout beliefs. These higher spreads and shifted exposures coincide with a persistent compression in asset prices, confirming that lower expected bailouts raise banks' cost of capital, push them out of the riskiest assets, and re-allocate any residual downside risk squarely onto shareholders rather than creditors or taxpayers.

Contribution to the Literature.

1. **Bailouts and Risk-Taking:** (Kareken & Wallace 1978, Panageas 2010, Farhi & Tirole 2012, Chari & Kehoe 2016, Dovis & Kirpalani 2022)

2. **Measuring TBTF subsidy** (Veronesi & Zingales 2010, Schweikhard & Tsesmelidakis 2011, Gandhi & Lustig 2015, Kelly et al. 2016, Hett & Schmidt 2017, Atkeson et al. 2019, Minton et al. 2019, Gandhi et al. 2020, Berndt et al. 2022, Haddad et al. 2023)

3. **Intermediary asset pricing** (He & Krishnamurthy 2013, Brunnermeier & Sannikov 2014, Garleanu & Pedersen 2011, Adrian & Boyarchenko 2012, Krishnamurthy & Muir 2017)

4. **Quantitative models of bank regulation** (Van den Heuvel 2008, Corbae & D'Erasmo 2019, Mendicino et al. 2019, Begenau 2020, Elenev et al. 2021)

Layout. This paper is organized as follows. Section 2 lay down a simple valuation framework to estimate the risk-neutral losses given default from option prices and CDS spreads. Section 3 documents the time series properties of expected losses and their correlation with fundamentals. Section 4 presents the model, section 5 characterizes the property of the equilibrium and section 6 calibrates it to US data. Section 7 decomposes observed spreads into bailout, fundamental and regulation components and measures the contribution of intermediaries leverage choices. Section 8 tracks how bailout expectations and capital regulation changed banks' risk exposures and cost of capital. Section 9 concludes.

2 Measuring Expected Losses Given Default

In this section, I present a conceptual framework to infer the risk-neutral losses given default from option prices and CDS contracts. The model considers a bank whose assets generate cash flows allocated between debt and equity, with default occurring when these cash flows are insufficient to meet debt obligations. Upon default, equity is completely wiped out, while debt holders may be protected by a government bailout, ensuring full repayment. I then show how to back out the risk-neutral probability of default from American put options on the bank's equity following Carr & Wu (2011), and how to extract the risk-neutral losses given default from CDS spreads.

2.1 Pricing Debt, Equity, and the Credit Spread

Let A_t be the market value of the bank's assets at date t and let δ_t denote the cash-flow rate (interest and principal) produced by those assets over $[t, t+1)$. Expectations $\mathbb{E}_t^*[\cdot]$ are taken under the risk-neutral measure, and $R_{f,t}$ is the one-period gross risk-free rate observed at t.

The risk-neutral present value of the asset cash flows is

$$V_t \;=\; \frac{1}{R_{f,t}}\,\mathbb{E}_t^*\Big[\sum_{\tau=t+1}^{\infty} \delta_\tau A_\tau\Big].$$

Denote by D_t the face value of debt outstanding and by P_t^D the contractual repayment rate (interest plus amortization) per unit of face value due at t. Default occurs when current asset cash flow cannot cover the payment:

$$\Delta_t \;=\; \mathbf{1}_{\{\delta_t A_t < P_t^D D_t\}}.$$

If default takes place, the government repays debtholders with probability π_t; if it does not intervene, debtholders recover $\hat{V}_t \leqslant P_t^D D_t$. Hence the payoff per unit of face value is

$$\widetilde{P}_t^D \;=\; (1-\Delta_t)P_t^D \;+\; \Delta_t\big[\pi_t P_t^D + (1-\pi_t)\hat{V}_t/D_t\big].$$

The market value of the debt equals the discounted stream of these payoffs:

$$S_t^D \;=\; \frac{1}{R_{f,t}}\,\mathbb{E}_t^*\Big[\sum_{\tau=t+1}^{\infty} \widetilde{P}_\tau^D\Big].$$

Equityholders receive what is left once the scheduled debt payment is met; they get nothing in default:

$$\widetilde{P}_t^E \;=\; (1-\Delta_t)\big[\delta_t A_t - P_t^D D_t\big]^+, \qquad S_t^E \;=\; \frac{1}{R_{f,t}}\,\mathbb{E}_t^*\Big[\sum_{\tau=t+1}^{\infty} \widetilde{P}_\tau^E\Big].$$

Because equity is wiped out at the first default event, it is economically equivalent to a perpetual American call on the firm's asset value that is cancelled if the debt payment cannot be met. Adding debt and equity then gives

$$S_t \;\equiv\; S_t^D + S_t^E \;=\; V_t \;+\; \underbrace{\mathbb{E}_t^*\Big[\sum_{\tau=t+1}^{\infty} \pi_\tau \Delta_\tau\big(P_\tau^D D_\tau - \hat{V}_\tau\big)\Big]}_{\text{value of implicit government guarantee}}\;,$$

so the state subsidizes debtholders by writing a digital put that fills any repayment shortfall in default states.

Credit spread decomposition. Define the risk-free discount factor from t to τ as

$$\beta_{t,\tau} = \prod_{s=t}^{\tau-1} \frac{1}{R_{f,s}},$$

and the promised contractual debt cash flow at $\tau \geqslant t+1$ as $C_\tau = P_\tau^D D_\tau$. I can the rewrite the default indicator and post-default payoffs as

$$\Delta_\tau = \mathbf{1}_{\{\delta_\tau A_\tau < C_\tau\}}, \qquad \widetilde{P}_\tau^D = C_\tau - (1-\pi_\tau)\big(C_\tau - \hat{V}_\tau\big)\Delta_\tau.$$

Hence, the market price of debt is

$$S_t^D = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}_t^*[\widetilde{P}_\tau^D] = \underbrace{\sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}_t^*[C_\tau]}_{\equiv A_t} - \underbrace{\sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}_t^*\big[(1-\pi_\tau)(C_\tau - \hat{V}_\tau)\Delta_\tau\big]}_{\equiv L_t}$$

where A_t risk-free present value of promised coupons and L_t is the present value of expected losses. I am now ready to define the credit spread CS_t as the non-negative scalar s solving

$$S_t^D = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau} \frac{C_\tau}{(1+s)^{\tau-t}}.$$

Substituting $S_t^D = A_t - L_t$ gives

$$L_t = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}_t^*[C_\tau]\, \big[1 - (1+CS_t)^{-(\tau-t)}\big]. \tag{1}$$

I can further define the risk-neutral default probability

$$Q_{t,\tau}^* = \mathbb{E}_t^*[\Delta_\tau],$$

and the conditional loss-given-default

$$LGD_{t,\tau}^* = \mathbb{E}_t^*\big[(1-\pi_\tau)(C_\tau - \hat{V}_\tau) \mid \Delta_\tau = 1\big].$$

The single-period discounted expected loss is

$$\ell_{t,\tau} = \beta_{t,\tau}\, \mathbb{Q}^*_{t,\tau}\, \mathrm{LGD}^*_{t,\tau}, \qquad L_t = \sum_{\tau=t+1}^{\infty} \ell_{t,\tau}. \tag{2}$$

Equation (1) expresses L_t entirely in terms of observed credit spreads CS_t, the cash-flow schedule $\{C_\tau\}$, and discount factors $\{\beta_{t,\tau}\}$. I can rearrange (2) to get

$$\mathrm{LGD}^*_{t,\tau} = \frac{\ell_{t,\tau}}{\beta_{t,\tau}\, \mathbb{Q}^*_{t,\tau}} = \frac{\mathbb{E}^*_t[C_\tau]\left[1 - (1 + CS_t)^{-(\tau - t)}\right]}{\mathbb{Q}^*_{t,\tau}}, \tag{3}$$

delivering the risk-neutral loss-given-default for every maturity $\tau > t$. The final step is to use option prices on the equity to reveal the risk-neutral default probability embedded in the market's valuation of the American put contracts. Combining this probability with observable CDS spreads then backs out the market-implied LGD under the risk-neutral measure.

2.2 Back-Up of Default Probabilities from Option Prices

Following Carr & Wu (2011), the *asset value* process $\{A_t\}_{t \geqslant 0}$ of the bank follows defaultable displaced dynamics with a default *region*

$$A_t \in \left[A_l, A_h\right], \qquad 0 < A_l < D_t < A_h,$$

and default occurs the first time the lower threshold is breached:

$$\mathcal{T} = \inf\left\{t \geqslant 0 : A_t \leqslant A_l\right\}.$$

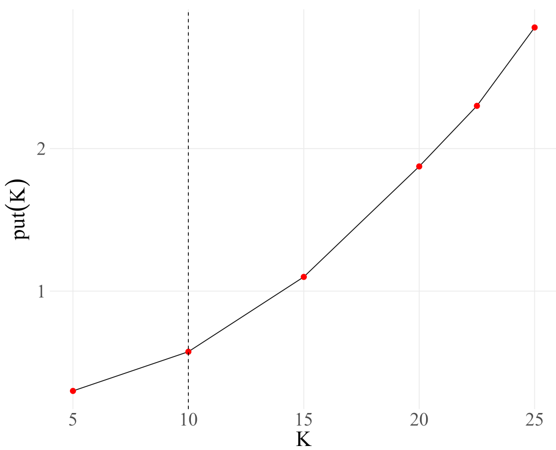
Such a region is natural when debt covenants and limited liability drive equity to zero at default yet keep it bounded above in normal times. For large regulated banks, capital requirements and stress tests narrow the "distance to default"; market capitalisation rarely drifts far beyond a plausible recapitalisation value, but once losses push assets below a regulatory threshold the stock price collapses. Hence the equity of major banks often trades within a tight corridor punctuated by crash events, qualitatively matching the setting here.

It is never optimal to exercise the American put on the bank's equity before default, because the exercise value $D_t - A_t$ is negative when the bank is solvent $(A_t > D_t)$. At default $(t = \mathcal{T})$ the equity value $S^E_t = (A_t - D_t)^+$ falls to zero, so immediate exercise yields K. Before default $(\mathcal{T} > t)$ equity is a cancelable call, bounded above by $\mathcal{E} := A_h - D_t > 0$. Choose any strike $K \in (0, \mathcal{E}]$; two cases obtain: (i) if no default occurs before maturity T

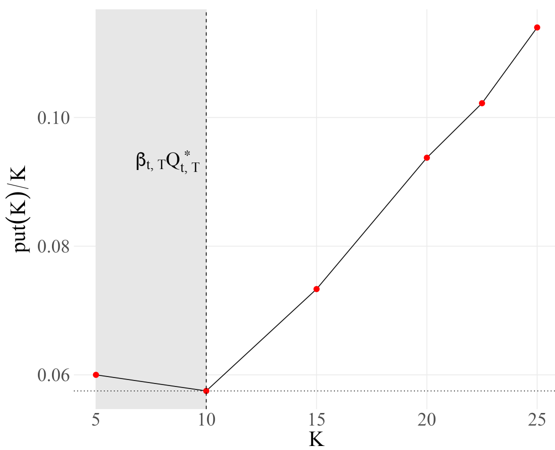
$(\mathcal{T} > T)$, the equity remains above $\mathcal{E}$ and the put expires worthless; (ii) if default happens $(\mathcal{T} \leqslant T)$, equity collapses and the put is exercised instantly. Thus the put payoff is a digital indicator of default scaled by K. Let $\mathrm{Put}_t(K, T)$ be the market price at $t \leqslant T$ and define the risk-free discount factor $\beta_{t,T} = \prod_{s=t}^{T-1} R_{f,s}^{-1}$. Under risk-neutral pricing

$$\mathrm{Put}_t(K, T) = \beta_{t,T}\, K\, \mathbb{E}_t^*\big[\mathbf{1}_{\{\mathcal{T} \leqslant T\}}\big] \equiv \beta_{t,T}\, K\, \mathbb{Q}_{t,T}^*, \quad \mathbb{Q}_{t,T}^* := \mathbb{E}_t^*\big[\mathbf{1}_{\{\mathcal{T} \leqslant T\}}\big], \qquad K \in (0, \mathcal{E}].$$

Figure 1 plots the American put price (panel 1a) and the corresponding return (panel 1b) for Morgan Stanley on 9 September 2008 $(T - t = 494$ days). The vertical line marks the estimated upper bound $\mathcal{E}$ of the default region. Inside that region the price–strike graph is *linear*; its slope equals $\beta_{t,T}\mathbb{Q}_{t,T}^*$ and is the shaded area beneath that line in panel (panel 1b). Outside the region the usual convex option profile re-emerges, reflecting dependence on pre-default equity dynamics.



(a) Put Value vs. Strike



(b) Option Return vs. Strike

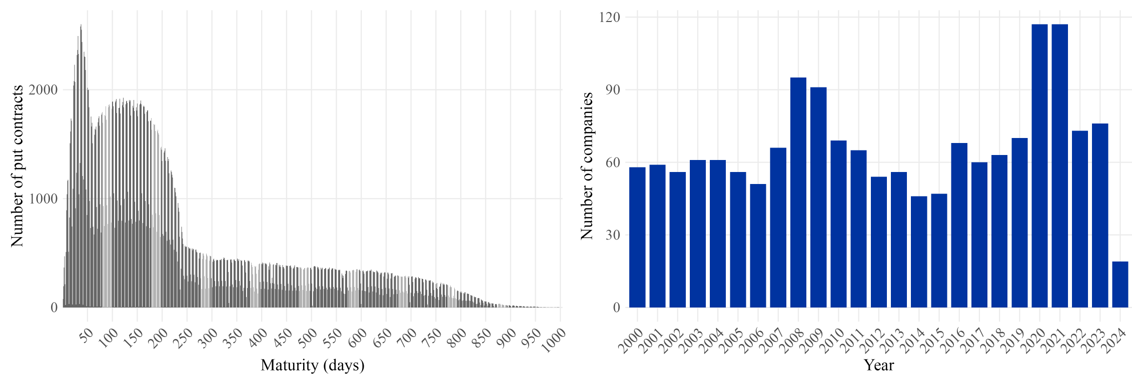
Figure 1: Put option price (a) and return (b) as a function of strike for Morgan Stanley on 09/09/2008, maturity 494 days. The vertical line marks the default-region upper bound $\mathcal{E}$. The shaded area represents the discounted risk-neutral default probability $\beta_{t,T}\mathbb{Q}_{t,T}^*$.

3 Empirical Implementation

3.1 Data

Data on CDS are obtained from IHS Markit. The initial sample consists of daily representative CDS quotes on all entities in the financial sector covered by Markit over the period from January 2000 through December 2022. While the five-year contract is generally thought to be the most liquid, I collect data on all maturities available for every company. When CDS rates are quoted for primary and non-primary coupons, I only retain the former. A similar rule is applied to the primary curve identifier. Whenever available, all CDS quotes are for a contractual definition of default known as "no restructuring". For losses given defaut, I source the average recovery taken from observed contributed recovery rate, which is sourced from the Markit CDS End of Day curve.

Options data are sourced from OptionMetrics. On each selected date, I examine the options data to identify companies with put options that satisfy the following criteria: (1) the bid price is greater than zero; (2) the offer price is greater than 0.05; (3) the offer price is no more than five times the bid price; (4) the open interest and the bid-ask spread are both greater than zero; (5) the absolute value of the put's delta does not exceed 15%; options prices are constructed as averages of highest closing bid and lowest closing ask prices. Equity options exhibit the greatest depth and liquidity at short maturities, especially within one year, while the benchmark CDS contract trades most actively at the five-year tenor. To align the two markets, I measure both option-implied and CDS-implied default risk at a common one-year horizon. The data from IHS Markit, OptionMetrics, and CRSP are merged based on the *permco* identifier for each bank.



(a) Number of put contracts by maturity (days)

(b) Number of companies over time

Figure 2: Panel (a) plots the number of chosen put options across different times to maturity. Panel (b) plots the number of companies in each year of sample period.

After all the filtering and cleaning, my final sample includes 48 banks from 2000 to 2023. The number of banks at each week ranges from around 30 to 100, with an average of 60 banks. The maturities of the chosen option contracts at the reference date range from 1 to 955 days, with an average of around 150 days. Panel 2b in Figure 2 plots the number of selected companies at each reference date of my sample period. The number of companies increased markedly since mid-2007, coinciding with the start of the financial crisis and again with the Covid19-crisis. Panel 2a in Figure 2 plots the number of selected put options contracts across different times to maturity.

Detecting the default boundary. The model assumes the existence of a default region $[0, \mathcal{E}]$, which the stock price cannot enter. The location of this region is unknown ex ante.

If American put prices were observable across a continuum of strikes at the same maturity, the default region would reveal itself because American put prices are linear in the strike price within the region. My core innovation lies in the adaptive detection of the default region $[0, \mathcal{E}]$. Beginning with the two lowest strikes $\{K_1, K_2\}$, the algorithm progressively expands the analysis window while maintaining statistical validity. For each time t, maturity T, and candidate window size m ranging from 2 to n, a no-intercept linear regression is estimated:

$$\mathrm{Put}\left(K_i\right) = \beta K_i + \epsilon_i \quad \text{for} \quad i = 1, \ldots, m.$$

The model's goodness-of-fit is quantified through a modified R^2 metric appropriate for regression through the origin:

$$R^2 = 1 - \frac{\sum_{i=1}^{m} \left(\mathrm{Put}\left(K_i\right) - \hat{\beta} K_i\right)^2}{\sum_{i=1}^{m} \mathrm{Put}\left(K_i\right)^2}.$$

Window expansion continues only while R^2 remains above a predetermined threshold $\tau = 0.98$. This process identifies the maximal strike K_{m*} where the linear pricing relationship holds, thereby defining the upper region boundary $\mathcal{E} = K_{m*}$. Within the identified region $\{K_1, \ldots, K_{m*}\}$, the parameter β is estimated via constrained least squares:

$$\hat{\beta} = \left(\sum_{i=1}^{m^*} K_i \cdot \mathrm{Put}\left(K_i\right)\right) / \left(\sum_{i=1}^{m^*} K_i^2\right)$$

This estimator represents the slope of the linear pricing relationship and corresponds to the risk-neutral default probability $\mathbb{Q}^*_{t,T}$, as derived from the fundamental pricing equation for default-contingent claims. For each CDS maturity, I linearly interpolate the the risk-neutral default probability to align with the maturity of the CDS contract. In Appendix A, I provide robustenness to my measure using the Thiel-Sen estimator. The Theil-Sen estimator, allows for robust estimation of the slope of the regression line even when there are large outliers in the underlying data. It also corresponds to a trading strategy, which is to invest in the strike pair i and j that deliver the median risk-neutral default probability. Buying the put of strike K_j and writing the put of strike K_i while yields a payoff of $K_j - K_i > 0$ if default happens. Because buying and writing these puts costs a total of $\mathrm{Put}(K_j) - \mathrm{Put}(K_i)$, normalized spread of this trading strategy earns exactly one dollar if default happens, corresponding to the Theil-Sen estimator.

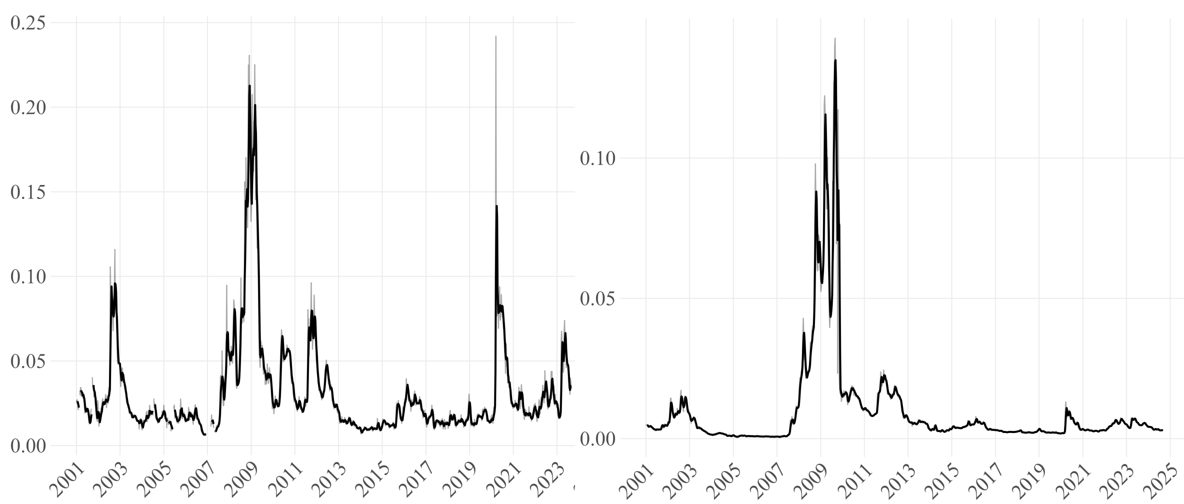
Table 1 reports the summary statistics of CDS spreads and default probabilities estimated from options for one-year maturity. The statistics show that CDS spreads and default probabilities are similar in average magnitudes and other statistical behaviors.

The estimates from the put options have a larger sample mean, median and a slightly larger standard deviation than the CDS spreads

Table 1: Summary Statistics for T = 365

	mean	median	std	min	max
$CS_{t,365}$	0.010	0.003	0.039	0.0001	0.994
$\mathbb{Q}^*_{t,365}$	0.038	0.025	0.043	0.003	0.575

Figure 3 plots the average risk neutral default probability $\mathbb{Q}^*_{t,T}$ and CDS spread $CS_{t,T}$ for T = 365 days. Default probabilities and spreads display strong comovements, especially after the Great Financial Crisis. Both series reach their peaks during the GFC but while default Probabilities come back to their pre-GFC levels, CDS spreads remain elevated. Remarkably, the Covid-19 crisis is associated with a spike in default probabilities but a very modest increase in CDS spreads if compred to GFC.



(a) Average $\mathbb{Q}^*_{t,T}$ for T = 365

(b) Average $CS_{t,T}$ for T = 365

Figure 3: Panel (a) shows default probabilities at 365 days (gray) and the 4 week moving average (black). Panel (b) shows CDS spreads at 365 days (gray) and the 4 week moving average (black).

3.2 Expected Losses Given Default

Starting from Equation (3) one can back out $LGD^*_{t,\tau}$ from the option-implied default probability $\mathbb{Q}^*_{t,\tau}$ and the CDS spread CS_t provided the following simplifying assumptions hold:

1. Single-period horizon. Set $\tau = t + 1$. Multi-period CDS contracts are rolled into a one-year par spread, so the term $(\tau - t) = 1$.

2. Par coupon schedule. The reference bond underlying the CDS is assumed to trade at par with unit face value: $\mathbb{E}_t^*[C_{t+1}] = 1$.

3. Small-spread approximation. For annualised spreads of a few hundred basis points,

$$1 - (1 + CS_t)^{-1} = \frac{CS_t}{1 + CS_t} \simeq CS_t.$$

4. Independence of recovery and timing. Expected recovery $\hat{V}_{t+1}$ is conditionally independent of default timing within the one-year window, consistent with standard CDS pricing conventions.

Under (1)–(3), the numerator of (3) reduces to $CS_{t,T}$, yielding the compact relationship

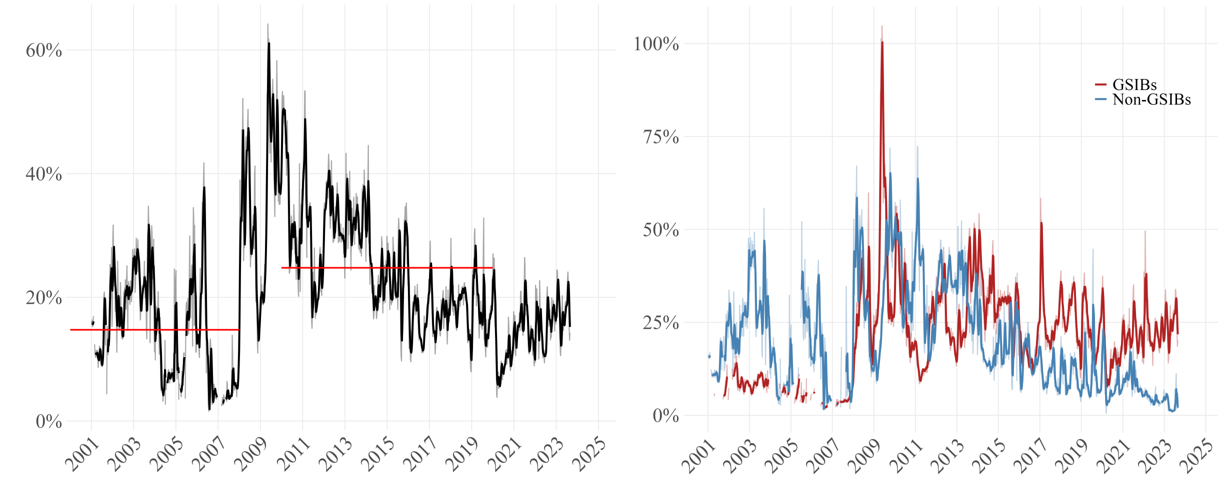
$$\mathrm{LGD}_{t,T}^* \simeq \frac{CS_t}{Q_{t,T}^*} \tag{4}$$

$Q_{t,t+1}^*$ is recovered from deep-out-of-the-money American-put prices on the bank's equity using the procedure in Section 2.2. CS_t is the one-year par CDS premium for the same reference entity. Given these two market observables, (4) delivers a risk-neutral loss-given-default that is internally consistent with both the option and CDS markets.

Panel 4a of Figure 4 plots the time series of the average $\mathrm{LGD}_{t,T}^*$ for $T = 365$ days. $\mathrm{LGD}_{t,T}^*$ varies strongly with business conditions, consistent with the relation between losses-given-default and market fundamentals. In particular, the variation in $\mathrm{LGD}_{t,T}^*$ implies that losses are low to values of approximately 10% during the economic recovery of the mid-2000s. They increase sharply to around 40% with the financial crisis of 2007-2009, and then gradually rise. The secondary increase in 2011 is contemporaneous with the downgrade of U.S. debt. After 2012 the expected losses hover around 30% to then gradually dropping to 10% from 2017 onwards. In addition, if default probabilities are coutercyclical and so are expected losses, note that estimates of default probability taken from CDS under the assumption that recoveries are constant would result in default probability that are more volatile and right-skewed, than estimates taken from option prices. Panel 4b of Figure 4 shows that the average expected losses for GSIBs are lower than non-GSIBs pre-GFC but higher post-GFC. This is consistent with the narrative of Berndt et al. (2022) (among others) of a structural shift in expected bailout probability for GSIBs after Dodd-Frank.

3.3 Liquidity-adjusted Expected Losses

Differences in risk-neutral default probabilities from options and CDS spreads may reflect variation in losses given default, but they could also result from market frictions. Out-



(a) Average $LGD^{*}_{t,T}$ for $T = 365$ days

(b) Average $LGD_{t,T}$ for $T = 365$ for GSIBs and non-GSIBs.

Figure 4: Panel (a) shows expected Losses for a 365-day maturity at weekly frequency (grey line) and 4-weeks moving average (black line). The red horizontal lines represent the averages pre-2008 and post-2010. Panel (b) shows expected losses for GSIBs (red) and non-GSIBs (blue) at weekly frequency with 4-weeks moving average.

of-the-money options used to estimate risk-neutral moments and option-implied default probabilities may be thinly traded. Similarly, the liquidity of some CDS contracts is low. Therefore, the observed decrease in losses given default during crises may instead reflect changes in market liquidity. The approximate relation between CDS spreads, option-implied default probabilities, and losses given default, discussed in Section 3, implies that, in the absence of market frictions, the ratio between the CDS spread and the default probability approximates the losses given default. To examine the extent to which market liquidity influences this relationship, I estimate the variation in this difference as a function of liquidity measures.

Illiquidity in the CDS and options markets may reflect both security-specific and market-wide factors. For options, I utilize bid-ask spreads, open interest, and volume as liquidity measures. Since default probabilities derived from options primarily depend on out-of-the-money options, I compute SPREAD^{O}_{t}, the average percentage bid-ask spread for such options. Additionally, VOL^{O}_{t} and OPEN^{O}_{t} represent the sum of volume and open interest for these contracts. For CDS, I measure bank-specific depth using DEPTH^{C}_{t} for five-year contracts and assume that depth of contracts at each maturity is correlated with five-year depth.

Aggregate liquidity is captured by combining the Treasury-Eurodollar (TED) spread, defined as the difference between the 90-day LIBOR and the 90-day Treasury Bill yield until 2022, with the difference between the 90-day SOFR and the 90-day Treasury Bill yield thereafter. I define that as $\mathsf{FinStress}_{t}$ An increase in the spread signals increased interbank counterparty credit risk and reduced funding liquidity. This data is obtained from the Federal Reserve. Additionally, equity market liquidity is proxied using the VIX index, VIX_t, as higher VIX levels are associated with larger risk premiums and reduced liquidity provision in equity markets (Nagel 2012). Data on the VIX is also sourced from the Federal Reserve.

I examine liquidity effects on the expected losses by regressing changes in the (log) expected losses on changes in the (log) liquidity variables at the aggregate level for every maturity T following Conrad et al. (2020):

$$\begin{aligned}\Delta\log(LGD^*_{t,T}) = a_T &+ b_1\Delta\log \mathsf{FinStress}_t + b_2\Delta\log VIX_t + b_3\Delta\log \mathsf{SPREAD}^O_{t,T} \\ &+ b_4\Delta\log \mathsf{VOL}^O_{t,T} + b_5\Delta\log \mathsf{OPEN}^O_{t,T} + b_6\Delta\log \mathsf{DEPTH}^C_{t,T} + e_{t,T}. \qquad (5)\end{aligned}$$

Using the residuals from this regression, I construct a liquidity-adjusted measure of expected losses. Specifically, $L\tilde{G}D^*_{t,T}$ is calculated by cumulating the residuals:

$$L\tilde{G}D^*_{t,T} = \exp\left(\hat{a}_T + \sum_{j=0}^{t}\hat{e}_{t-j,T}\right),$$

where $L\tilde{G}D^*_{t,T} = LGD^*_{t,T}$ at $t = 1$ (January 2000), and each period's value incorporates the residual from the regression above.

Figure 5 plots the time series of $L\tilde{G}D^*_{t,T}$ and $LGD^*_{t,T}$ for $T = 365$ days. $L\tilde{G}D^*_{t,T}$ closely tracks the original $LGD^*_{t,T}$ before the financial crisis, but differs significantly after. $L\tilde{G}D^*_{t,T}$ is higher than $LGD^*_{t,T}$ beginning approximately in 2009. That is, adjusting for liquidity effects results in an estimate of expected losses $L\tilde{G}D^*_{t,T}$ that is meaningfully higher during the financial crisis and in its aftermath. This suggests that fundamentals and liquidity effects are not fully reflected in the original expected losses before the crisis, but that the liquidity-adjusted expected losses are divergent from the original expected losses after the crisis suggesting the increased role of fundamentals and bank specific factors in the pricing of expected losses. Overall, estimates of loss given default that control for liquidity effects are more sensitive to economic states than measures that do not control for liquidity.

3.4 The Role of Regulation post-2010

In this section I study whether post-crisis bank regulation tightened the mapping between equity–tail volatility and default premia by estimating the change in the fixed-effect partial correlation between daily logarithmic CDS spreads and the logarithm of model-free

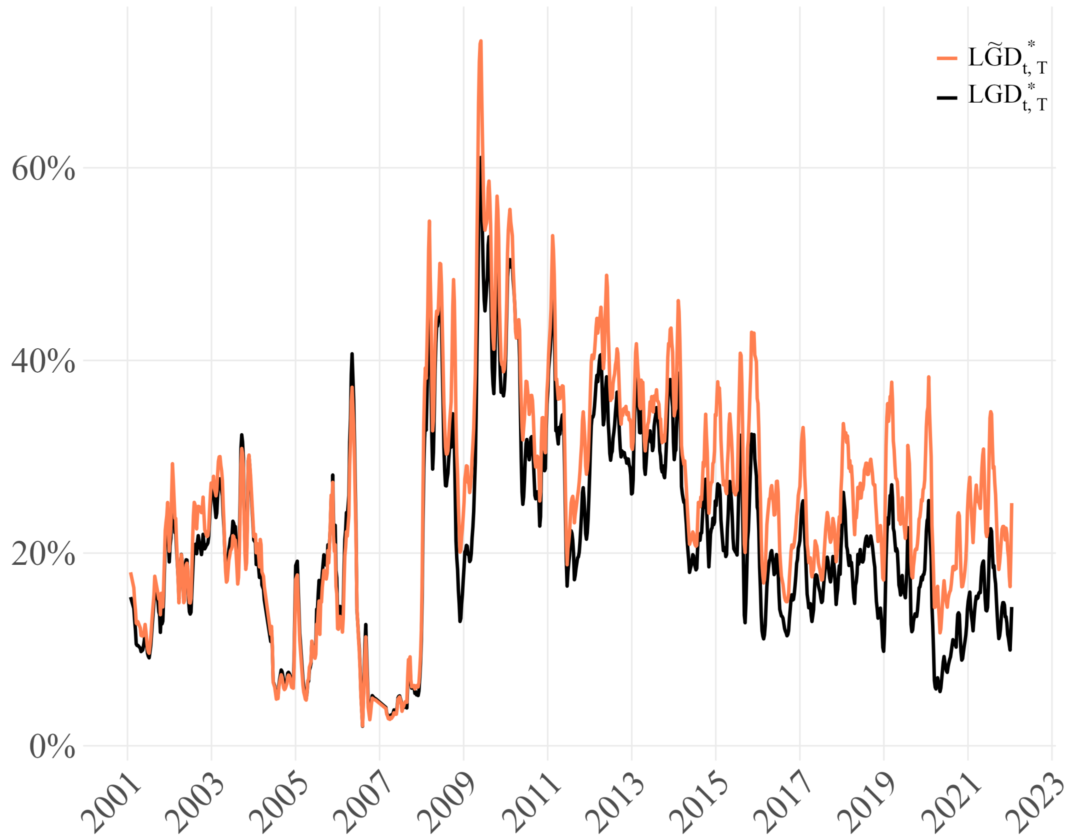


Figure 5: Original expected losses versus liquidity adjusted at weekly frequency for maturity of 365 days.

risk-neutral variance of equity returns calculated from option prices as

$$\mathrm{Var}_{t,T} = \frac{2}{(T-t)R_{f,t}\left(S_t^E\right)^2}\left[\int_0^{F_{t,T}} \mathrm{put}_t(K,T)\,dK + \int_{F_{t,T}} \mathrm{call}_t(K,T)\,dK\right]$$

where $F_{t,T}$ is the forward price of the equity at time t for maturity T, $R_{f,t}$ is the risk-free rate at time t, and S_t^E is the equity price at time t.

The main idea behind identification is that bailout and regulation move credit spreads and equity tail volatility in the opposite direction. A drop in bailout probability leads to higher credit spreads and lower equity tail volatility while a tightening of regulation leads to lower credit spreads and higher equity tail volatility. While both bailout and regulation are aimed at reducing the risk of default, they have different implications for credit spreads. The identification strategy is to estimate the change in the partial correlation between CDS spreads and equity tail volatility before 2008 and after 2010. For this reason, I drop the acute stress window 2008–2009. I average quotes across option maturities per bank–day and split the panel at 1 January 2010. I first residualise both series,

$$u_{it}^{CS} = \log\big(CS_{it}\big) - \widehat{\alpha}_i - \widehat{\delta}_t, \qquad u_{it}^{Var} = \log\big(\mathrm{Var}_{t,T}\big) - \widehat{\alpha}_i - \widehat{\delta}_t, \tag{6}$$

and standardise them within each era so that $z_{it}^{(\cdot)} = (u_{it}^{(\cdot)} - \bar{u}_e)/\sigma_e$. The era-specific partial correlations are obtained through the regression

$$z_{it}^{CS} = \rho_0\, z_{it}^{Var} + \Delta\rho\, z_{it}^{Var}\, \mathbf{1}\{t \geqslant 2010\text{-}01\text{-}01\} + \varepsilon_{it}, \tag{7}$$

with standard errors clustered by bank; because both regressors have unit variance, ρ_0 equals the pre-crisis correlation and $\Delta\rho$ is its post-crisis change. Table 2 reports the results of the regression (7). The estimation yields $\rho_{pre} = 0.271$ and $\rho_{post} = 0.367$, implying $\Delta\rho = 0.096$. After Basel III's capital and resolution reforms, a one-standard-deviation increase in risk-neutral equity variance now produces a roughly 35% larger proportional change in CDS spreads than before the crisis, indicating that markets price downside equity volatility more strongly into default premia in the post-2010 regime, consistent with tighter loss-absorbing regulation.

4 Model

4.1 Environment

Time is infinite, discrete and indexed by t. The economy is populated by households, indexed by H; a continuum of intermediaries, denoted by I; and a government.

Dependent Variable:	z^{CS}_{it}
Variables	
z^{Var}_{it}	0.1164***
	(0.0314)
$z^{Var}_{it} \times$ post	0.2507*
	(0.1254)
$z^{Var}_{it} \times$ pre	0.1548
	(0.1604)
Fit statistics	
Observations	45,384
R^2	0.11177
Adjusted R^2	0.11173

Clustered (permco) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: The table reports the results of the regression (7).

Preferences. Households have Epstein-Zin preferences over utility streams $\{C_t\}_{t=0}^{\infty}$ with intertemporal elasticity of substitution ν and risk aversion σ

$$V_t = \left\{ (1-\beta)\left(C_t\right)^{1-1/\nu} + \beta \left(\mathbb{E}_t \left[\left(V_{t+1}\right)^{1-\sigma} \right] \right)^{\frac{1-1/\nu}{1-\sigma}} \right\}^{\frac{1}{1-1/\nu}}, \tag{8}$$

with discount factor β.

Technology. The economy contains a constant measure of Lucas trees, indexed by $i \in [0,1]$ for each island j. In island j, tree i delivers the period-t payoff

$$y_t^{i,j} = z_t^i \, \omega_t^j \, Z_t \, e^{-\zeta d_t}, \tag{9}$$

where $z_t^i > 0$ is a firm-specific productivity shock, $\omega_t^j > 0$ is an island shock, $Z_t > 0$ represents aggregate productivity, and $d_t \in \{0,1\}$ indicates a disaster state. The multiplicative structure implies that each shock scales output proportionally, while disasters reduce output by the factor $e^{-\zeta}$.

To guarantee positivity of (9), the two idiosyncratic shocks are modelled as log-normal such that

$$\ln z_t^i = \sigma^z \varepsilon_t^i, \quad \ln \omega_t^j = \sigma^\omega \eta_t^j, \tag{10}$$

with $\varepsilon_t^i, \eta_t^j \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,1)$. The parameters σ^z and σ^ω pin down the cross-sectional dispersion of firm and island shocks, respectively. Let $g(\cdot)$ and $f(\cdot)$ denote their log-normal density functions respectively.

Aggregate productivity follows a log-AR(1) process,

$$\ln Z_t = \rho \ln Z_{t-1} + (1-\rho)\mu + \sigma\varepsilon_t, \tag{11}$$

where $\varepsilon_t \sim \mathcal{N}(0,1)$, μ is the long-run mean of $\ln Z_t$ (normalised to unity), $\rho \in (0,1)$ governs persistence, and $\sigma > 0$ controls aggregate volatility.

The binary disaster indicator evolves according to the Markov transition matrix

$$\mathbb{P}_d = \begin{pmatrix} 1-\pi_d & \pi_d \\ 1-\pi_s & \pi_s \end{pmatrix}, \tag{12}$$

so that π_d is the probability of entering a disaster when the economy is currently normal, and π_s is the probability of remaining in disaster once one has occurred.

Each tree backs a single unit of long-term debt with face value 1, market price p_t, amortisation rate $\delta \in (0,1)$, and coupon c. The promised period-t cash flow is therefore $c + (1-\delta) + \delta p_t$. Default occurs whenever the realised payoff in (9) is insufficient, i.e. when $y_t^{i,j} < c + (1-\delta)$. Credit markets are segmented so intermediaries cannot *across* across islands, the firm-specific productivity shocks z_t^i diversify *within* an island, generating cross-sectional heterogeneity in loan-portfolio returns (Mendicino et al. 2019). The period-t return on its loan portfolio, conditional on its own shock ω_t, is

$$\mathcal{P}_t(\omega_t) = \left[c + (1-\delta) + \delta p_t\right] \int_{\underline{z}(\omega_t, Z_t, d_t)}^{\infty} g(z)\, dz \; + \; (1-\eta)\omega_t Z_t e^{-\zeta d_t} \int_0^{\underline{z}(\omega_t, Z_t, d_t)} z\, g(z)\, dz, \tag{13}$$

where the default threshold solves $y_t^{i,j} = c + (1-\delta)$:

$$\underline{z}(\omega_t, Z_t, d_t) = \frac{c + (1-\delta)}{\omega_t\, Z_t\, e^{-\zeta d_t}}. \tag{14}$$

The first term in (13) represents performing loans that deliver the full contractual payment; the second captures recoveries from defaulted loans, which transfer a portion $1-\eta$ of the realised tree payoff to debtholders. Intermediaries receive no upside: modeling intermediairies assets as debt contracts captures the concave, "capped" payoff profile that is central to their risk dynamics. This structure implies that asset volatility rises sharply when collateral values fall, making equity volatility much more sensitive to downturns and causing standard models with constant-volatility lognormal assets to understate default probabilities in good times and misprice equity risk (Nagel & Purnanandam 2020).

The representative household holds the residual equity tranche of every tree and perfectly diversifies across i and j. Its period-t equity cash flow equals

$$\Pi_t = a_t \iint \left[y(z,\omega) - \left(c + (1-\delta) + \delta p_t\right)\right] \mathbf{1}_{\{y(z,\omega) \geqslant c+(1-\delta)\}} g(z)\, f(\omega)\, dz\, d\omega \; + \; p_{t+1}, \quad (15)$$

where a_t is the mass of trees operated per island. The integral is the residual payoff net of debt obligations, while p_{t+1} is the market value of debt carried into the next period.

I now describe intermediaries and households' problems as well as the government in more detail. The full set of Bellman equations and first-order conditions is relegated to Appendix B. I denote by $\mathbf{S}_t$ the vector that collects the current values of the exogenous state variables, to be defined explicitly later on; $\mathbf{S}_{t+1}$ denotes next period's state vector.

4.2 Intermediaries

I now describe the optimization problem of intermediaries. Intermediaries choose the amount of assets to purchase for next period a_{t+1} and the amount of deposits to issue to households d^I_{t+1} at price $q^d_t = \frac{1}{1+r^d_t}$ and bonds b^I_{t+1} price $q_t = \frac{1}{1+r_t}$. The government fully insures deposits and bails out bond-holders with probability $\pi_t = \frac{\exp\{\tilde{\pi}_t\}}{1+\exp\{\tilde{\pi}_t\}}$, and

$$\tilde{\pi}_t = \bar{\pi}(1-\rho^\pi) + \rho^\pi \tilde{\pi}_{t-1} + \sigma^\pi \varepsilon^\pi_t, \quad \varepsilon^\pi_t \sim \mathcal{N}(0,1).$$

Moreover, banks have a payout target that is fraction ϕ_0 of net worth, n_t. They can deviate from this target and raise additional equity e_t that is, pay out $\phi_0 n_t - e_t$, but this comes at a cost $\frac{\phi_1}{2}\left(\frac{e_t}{n_t}\right)^2 n_t$.

4.2.1 Timing

The timing of events is as follows:

1. Aggregate shocks $\mathbf{S}_t$ are realized.
2. Idiosyncratic payoff shocks of intermediaries are realized. Default decisions follow.
3. Banks choose their portfolios. Surviving intermediaries pay dividends, and new intermediaries are set up to replace liquidated bankrupt intermediaries.
4. Government insures all defaulting deposits while bonds are bailed out with probability π_t.
5. Households consume.

4.2.2 Portfolio Problem

At Step 3 of the intraperiod sequence of events, intermediaries solve a portfolio choice problem. In Appendix B.2.1, I show that at the time banks choose their new portfolio, all banks have the same value and face the same optimization problem. They choose how much assets to buy for next period, a_{t+1}, how much equity to issue, e_t and how many bonds and deposits to issue, b^I_{t+1}, d^I_{t+1}, to maximize current period dividend payout to shareholders and the continuation value. The dividend of an indivudual intermediary to its shareholders at Step 5 is given by

$$\varpi_t = \phi_0 n_t - e_t - \frac{\phi_1}{2}\left(\frac{e_t}{n_t}\right)^2 n_t.$$

The intertempotal budget constraint of the bank is

$$(1-\phi_0)n_t + e_t + \left(q^d_t - \kappa\right) d^I_{t+1} + q_t\left(d^I_{t+1}, b^I_{t+1}, a_{t+1}\right) b^I_{t+1} = p_t a_{t+1}. \tag{16}$$

The first two terms represent the retained earnings and new equity issued by the bank. The third and fourth term denote new funds from deposits and bond issuance at prices $q_t\left(d^I_{t+1}, b^I_{t+1}, a_{t+1}\right)$ and q^d_t (net of the deposit insurance fee κ and liquidity premium α_d). The fifth term is new capital purchased at price p_t. The last term denotes the deposit adjustment costs.

Finally, I define intermediary net worth as $n_t = \mathcal{P}_t(\omega_t)a_t - d^I_t - b^I_t$. The first term denotes the payoff of capital after the realization of the island shock ω_t. The second and third term denote deposit and bond repayment obligations.

I characterize the bank's portfolio problem recursively using the value function $V(n_t; \mathbf{S}_t)$. Intermediaries discount future payoffs by $\mathcal{M}_{t,t+1}$, which is the stochastic discount factor of households, their equity holders. The value of surviving bank is

$$V(n_t; \mathbf{S}_t) = \max_{a_{t+1}, b^I_{t+1}, d^I_{t+1}, e_t} \varpi_t + \mathbb{E}_t\left[\mathcal{M}_{t,t+1} \max\left\{V(n_{t+1}; \mathbf{S}_{t+1}), 0\right\}\right] \tag{17}$$

subject to the budget constrait (16) and the capital requirement constraint

$$b^I_{t+1} + d^I_{t+1} \leqslant \xi p_t a_{t+1}, \tag{18}$$

and that $d^I_{t+1} \leqslant \bar{D}_t$, where $\bar{D}_t$ is the maximum amount of deposits that can be issued by the intermediary. This constraint captures the in a tractable way the fact that intermdiaries faces costs of running their deposit business, such as the cost of maintaining a branch network, and thus cannot issue unlimited deposits despite being the least costly source of funding. I assume that the maximum deposit capacity is time-varying and follows a log-AR(1) process

$$\ln \bar{D}_t = \rho^{\bar{D}} \ln \bar{D}_{t-1} + (1 - \rho^{\bar{D}})\bar{D} - \zeta^{\bar{D}} \ln(Z_t e^{-\zeta d_t}) + \sigma^{\bar{D}} \varepsilon_t^{\bar{D}}, \tag{19}$$

where $\varepsilon_t^{\bar{D}} \sim \mathcal{N}(0,1)$ and the coefficient $\zeta^{\bar{D}}$ governs the negative correlation between deposit demand and the business cycle and captures the fligh to safety events during economic downturns. Intermediaries pay deposit insurance fees κ to the government per unit of deposits. They internalize that the price of their debt, $q_t\left(b_{t+1}^I, d_{t+1}^I, a_{t+1}\right)$, is a function of their default risk and thus their capital structure. The continuation value takes into account the possibility of optimal default, in which case equity holders get zero. Constraint (18) is a Basel-style regulatory bank capital constraint, and requires that deposits are collateralized by intermediaries portfolio. The parameter ξ determines how much debt can be issued against each dollar of assets. I have chosen to have market prices on the right-hand side of (18) because levered financial intermediaries face regulatory constraints that depend on market prices.

4.2.3 Aggregation and bankruptcy

Two properties of the bank problem allow me to obtain aggregation. First, island shocks ω_t are uncorrelated over time. Second, the value function is homogencous of degree one in net worth n_t. I use these properties to write the bank value function in terms of the value per unit of wealth $v(\mathbf{S}_t) = V(n_t; \mathbf{S}_t)/n_t$, which only depends on the aggregate state vector $\mathbf{S}_t$.

At the beginning of each period, a fraction of intermediaries defaults before paying dividends to shareholders and choosing the portfolio for next period. Debt holders and the government take ownership of these bankrupt intermediaries and liquidate them to recover some of the outstanding debt. Bankrupt intermediaries are replaced by newly started ones that households endow with initial equity n^0 per bank. These new intermediaries then solve problem (17) with $n_t = n^0$.

Denote aggregate net worth of surviving and newly started intermediaries by N_t, and the ratio of new equity over net worth as $\tilde{e}_t = e_t/n_t$. This ratio is identical across intermediaries due to scale invariance. Then the aggregate dividend to households is:

$$\Pi_t^{\text{div}} = N_t \left(\phi_0 - \tilde{e}_t - \frac{\phi_1}{2} (\tilde{e}_t)^2 \right) - F(\omega_t^*) n^0$$

The dividend has two parts: (i) all intermediaries, both surviving and newly started, pay a dividend share $\phi_0 - \tilde{e}_t$ net of costs, out of their net worth, and (ii) newly started intermediaries, equal in mass to bankrupt firms $F_t \equiv F(\omega_t^*)$, receive initial equity n^0. Banks optimally default at step 4 in the intra-period time line when $\omega < \omega^*$, such that

$$\mathcal{P}_t(\omega^*)a_t - d_t^I - b_t^I = 0.$$

I define $\mathcal{D} \equiv \{\omega : \omega < \omega^*\}$ as the set of defaulting intermediaries and $\mathcal{D}^c$ as the set of non-defaulting intermediaries.

4.3 Household

Each period, households receive the payoffs from owning all equity and debt claims on intermediaries and trees, yielding financial wealth W_t. They further pay taxes T_t. Houscholds choose consumption C_t, deposits and bonds, d_{t+1}^j and B_{t+1}^H to maximize utility (8) subject to their inter-temporal budget constraint

$$W_t - T_t \geqslant C_t + q_t B_{t+1}^H + q_t^d D_{t+1}^H, \tag{20}$$

where p_t denotes the market price of bank equity. The transition law for houschold financial wealth W_t is given by

$$W_t = \Pi_t + \Pi_t^{div} + D_t^H + B_t^H \left[\int_{\omega \in \mathcal{D}_t^c} 1 dF(\omega) + \int_{\omega \in \mathcal{D}_t} (\pi_t + (1-\pi_t) RV_t(\omega))\, dF(\omega), \right] \tag{21}$$

where $\mathcal{D}$ is the set of defaulting intermediaries, and $\mathcal{D}^c$ is the set of non-defaulting intermediaries, as defined above, and $RV_t(\omega)$ is the bonds recovery value of the defaulting intermediaries given by

$$RV_t(\omega) \equiv \frac{\max\{(1-\chi)A_t \mathcal{P}_t(\omega) - D_t^I, 0\}}{B_t^I}.$$

Finally, the deposit rate r_t^d may differ from the risk-free rate r_t^f to capture the fact that changes to risk-free rates do not pass through one-for-one to deposits[1] I model the relationship in reduced form as

$$r_t^d = \left(\bar{r}^f - \alpha_d\right) + \beta_d \left(r_t^f - \bar{r}^f\right),$$

with $\alpha \geqslant 0$ and $\beta_d \in (0, 1]$. The parameter α_d captures the average spread between risk-free and deposit rates, while β_d capture the degree of deposit rate sensitivity to risk-free

[1]While my paper does not directly study the role of interest rate risk in driving the banks' franchise value (Drechsler et al. 2017, Jiang et al. 2024, DeMarzo et al. 2024) it is important to account for the special role of deposits in the banking system and their contribution to banks cost of capital.

rate deviations from its mean. When $\alpha_d = 0$ and $\beta_d = 1$, the two rates are always equal.

4.4 Government

Defaulting intermediaries are liquidated by the government. During the bankruptcy process, a fraction χ of the asset value of intermediaries is lost. After the bankruptcy proceedings are completed, a new bank is set up to replace the failed one. This bank sells its equity to new owners and is otherwise identical to a surviving bank after asset payoffs.

The aggregate bailout payment of the government is:

$$\begin{aligned} TC_t = \pi_t \int_{\omega \in \mathcal{D}_t} & \left(1 - \frac{\max\{(1-\chi)A_t \mathcal{P}_t(\omega) - D_t^I, 0\}}{B_t^I}\right) B_t^I dF(\omega) \\ + \int_{\omega \in \mathcal{D}_t} & \left(1 - \frac{\min\{(1-\chi)A_t \mathcal{P}_t(\omega), D_t^I\}}{D_t^I}\right) D_t^I dF(\omega). \end{aligned} \tag{22}$$

I assume that the government runs a balanced budget so that

$$T_t + \kappa D_{t+1}^I = TC_t, \tag{23}$$

and bailouts are financed by lump-sum taxes to households.

4.5 Market clearings and equilibrium

The market clearing conditions for assets, stocks, debt and deposits are:

$$A_t = 1, \tag{24}$$

$$B_t^I = B_t^H, \tag{25}$$

$$D_t^I = D_t^H \tag{26}$$

Finally, the aggregate resource constraint reads

$$\begin{aligned} Z_t e^{-d_t \zeta} = C_t + \Phi^e\left(e_t / N_t\right) + \chi A_t & \int_{\omega \in \mathcal{D}_t} \mathcal{P}_t(\omega) f(\omega) d\omega \\ + \eta Z_t e^{-\zeta d_t} \int \int_0^{\underline{z}(\omega_t, Z_t, d_t)} & \omega z\, g(z) f(\omega)\, dz\, d\omega. \end{aligned} \tag{27}$$

I am now ready to define an equilibrium for the economy.

Definition 1. *Given aggregate shocks* $\{d_t, Z_t, \pi_t\}$, *a competitive equilibrium is an allocation* $\{C_t, B_{t+1}^H, D_{t+1}^H\}$ *for households,* $\{A_{t+1}, B_{t+1}^I, D_{t+1}^I, e_t\}$ *for intermediaries, a price vector* $\{p_t, q_t, q_t^d\}$, *and policy $\{T_t\}$ such that given the prices, households maximize lifetime utility, intermediaries maximize shareholder value, the government satisfies its budget constraint, and markets clear.*

5 Equilibrium Characterization

In this section, I first outline the key properties of the intermediary equilibrium capital structure and pricing functions for debt and assets. After that, I describe the behavior of credit spreads in response to changes in bailout expectations. All results are formally proven in a simplified version of my model economy in Appendix G.

5.1 Optimality Conditions

To fully understand the intermediaries' pricing conditions, it is useful to define the marginal value of net worth-that is, the shadow price μ_t attached to a dollar of equity injections. In my setup, letting $\tilde{e}_t \equiv e_t/N_t$ denote new equity issued relative to existing net worth, the intermediary's envelope condition can be written as

$$\nu(S_t) = \phi_0 + \frac{\phi_1}{2}\tilde{e}_t^2 + \mu_t(1 - \phi_0),$$

where $\nu(S_t)$ is the (scaled) value function and ϕ_0 is the target payout fraction. The first-order condition with respect to equity issuance pins down μ_t:

$$\mu_t = 1 + \phi_1 \tilde{e}_t$$

Dividing the envelope condition through by μ_t gives a compact expression for the "marginal value" of net worth:

$$\tilde{\nu}(S_t) \equiv \frac{\nu(S_t)}{\mu_t} = \frac{\phi_0}{1 + \phi_1 \tilde{e}_t} + \frac{\phi_1}{2(1 + \phi_1 \tilde{e}_t)}\tilde{e}_t^2 + (1 - \phi_0)$$

When $\phi_1 = 0$ (no issuance frictions), $\mu_t \equiv 1$ and the marginal value reduces to $\phi_0 + (1 - \phi_0) = 1$. As $\phi_1 > 0$, issuing equity becomes costly: increasing $\tilde{e}_t$ raises the shadow value μ_t above one, so that each additional dollar of net worth is valued more highly and endogenous payout/ injection policies hinge on the trade-off between internal financing (at marginal value μ_t) and external issuance (priced at $\phi_0 + \phi_1 e_t$).

Debt choice. The choice of non-contingent debt is central to the analysis in that it endogenously pins down the solvency risk of the financial intermediary as a function of the undelying aggregate sources of risk and the intermediaries frictions. When choosing the quantity of non-contingent debt B^I_{t+1}, the intermediary balances the cheapness of debt financing against the expected cost of default. Formally, from the first order condition of the intermediary's with respect to B^I_{t+1}, I have

$$q_t = \lambda_t + \mathbb{E}_t \Bigg\{ \mathcal{M}_{t,t+1} \Bigg[\tilde{\nu}(S_t) \underbrace{(1 - F_{t+1})}_{\text{survival prob.}} + \underbrace{(1-\pi_{t+1}) \left(F_{t+1} RV^B_{t+1} + \frac{\partial F_{t+1}}{\partial B^I_{t+1}} (D^I_{t+1} + B^I_{t+1} - (1-\chi)\mathcal{P}_{t+1}(\omega^-_{t+1})) \right)}_{\text{default costs}} \Bigg] \Bigg\}. \tag{28}$$

On the left, q_t is the promised price of new debt. On the right, $\tilde{\lambda}_t$ reflects the tightness of the intermediary's leverage constraint (the shadow cost of a dollar of debt). The term $\tilde{\nu}(S_{t+1})(1 - F_{t+1})$ captures the marginal benefit when the intermediary survives—receiving full payoff at the shadow marginal value of net worth, discounted by the survival probability $1 - F_{t+1}$. With probability F_{t+1} the intermediary defaults; in that event, creditors suffer losses and the intermediary pays dead-weight costs. Intermediaries internalize through $\partial F_{t+1}/\partial B^I_{t+1}$ how additional debt tightens default likelihood and raises expected claims shortfall $\left(D^I_{t+1} + B^I_{t+1} - (1-\chi)\mathcal{P}_{t+1}\right)$. When the bailout probability is higher, the expected loss from default falls dollar-for-dollar. In effect, bailouts subsidize debt issuance by reducing the weight on default costs, tilting the trade-off in favor of borrowing as depicted in the left panel of Figure 6. In particular, the debt policy is more sensitive to the bailout probability π_t when the intermediary is more levered and the default probability is higher. Altogether, the intermediary issues debt up to the point where the marginal cheapness of debt q_t just offsets the sum of its shadow leverage cost, the foregone net-worth value in bad states, and the remaining, bailout-adjusted expected deadweight costs of default.

Asset pricing. The intermediary's choice of risky asset holdings A_{t+1} determines the expected returns and so the intermediary willingness to be exposed to fundamental aggregate risk. Formally, from the first-order condition of the intermediary with respect to

A_{t+1}, I have

$$p_t = \mathbb{E}_t \left\{ \frac{\mathcal{M}_{t,t+1}}{1-\lambda_t\,\xi} \Big[\tilde{\nu}\,(S_t)\,(1-F_{t+1})\mathcal{P}_{t+1}(\omega^{+}_{t+1}) \right.$$
$$\left. + \; (1-\pi_{t+1})\Big[F_{t+1}(1-\chi)\mathcal{P}_{t+1}(\omega^{-}_{t+1}) - \frac{\partial F_{t+1}}{\partial A_{t+1}}\big(D^I_{t+1} + B^I_{t+1} - (1-\chi)\mathcal{P}_{t+1}(\omega^{-}_{t+1})\big)\Big]\Big] \right\}. \tag{29}$$

On the left, p_t represents the price paid for the risky asset today. On the right, the first term represents the expected marginal benefit of acquiring an additional risky asset in states where the intermediary survives, evaluated at the shadow marginal value of net worth. The second term reflects the value of investment in default and no bailout states: the intermediary internalizes how additional asset exposure influences default likelihood ($\partial F_{t+1}/\partial A_{t+1} < 0$) and expected recovery values in default states This component pushes up the price of the risky asset. An increase in the bailout probability π_{t+1}, on one side, it reduces the expected default losses associated with riskier asset positions, incentivizing intermediaries to decrease their exposure to risk and decreasing their willingness to pay. This is mitigated by the effect that higher bailout probability has on debt choices as analized above and so on the default probability, shifitng valuations to default states. In particular, higher bailout probability props up the price of the risky asset by making leverage cheaper for the intermdiary and reducing their reliance on costly equity issuance. The net effect of higher bailout probability is to increase the price of the risky asset as depicted in the right panel of Figure 6.

5.2 Bailout Expectations and Credit Spreads

This section analyzes the impact of bailout expectations on credit spreads directly and indirectly through intermediaries' balance sheet choices. The credit spread on one-period defaultable debt is determined by the following equilibrium condition derived from the household's first order condition for debt:

$$\underbrace{r_t - r^{rf}_t}_{\text{Credit Spread}} = \underbrace{\mathbb{E}_t\left\{\mathcal{M}_{t,t+1}(1-\pi_{t+1})F_{t+1}\left[1 - RV^B_{t+1}\right]\right\}}_{\text{Expected Default Loss}} \tag{30}$$

Default losses embed three critical elements: the bailout probability π_{t+1} (government intervention likelihood), default probability F_{t+1}, and asset recovery rate RV^B_{t+1} per unit,

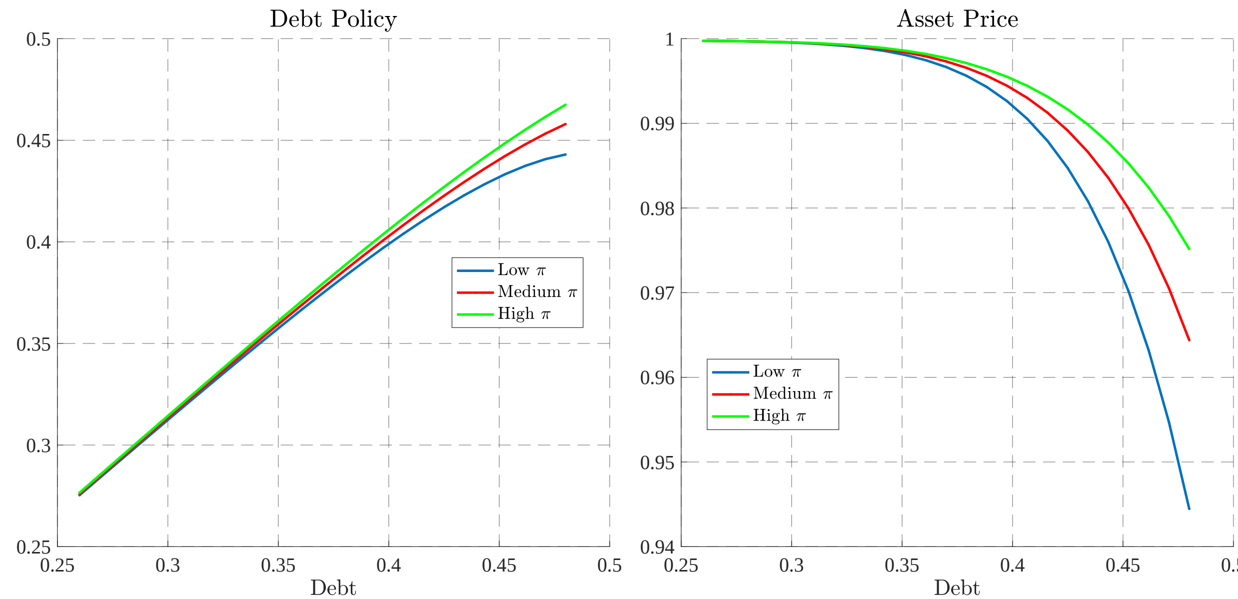


Figure 6: Policy functions evaluated at the ergodic means of D_t, Z_t, and d_t. Left: debt policy B_{t+1} as a function of debt B_t for three values of bailout probability π_t (baseline, low, and high). Right: asset price p_t as a function of B_t for the same three π_t levels.

conditional on default. First, I can rewrite the credit spread as:

$$r_t - r_t^{rf} = \mathbb{E}_t \left\{ \mathcal{M}_{t,t+1}(1-\pi_{t+1}) \left(\int_0^{\omega_{t+1}^*} 1 - \frac{\max\{(1-\chi)\mathcal{P}_{t+1}(\omega) - D_{t+1}^I, 0\}}{B_{t+1}^I} f(\omega) d\omega \right) \right\}.$$

The bailout probability π_{t+1} affects the credit spread $r_t - r_t^{rf}$ through two distinct channels in the model:[2]

$$\frac{\partial(r_t - r_t^{rf})}{\partial \pi_{t+1}} = \mathbb{E}_t \left\{ \mathcal{M}_{t,t+1} \left(\underbrace{(1-\pi_{t+1}) \frac{\partial B_{t+1}}{\partial \pi_{t+1}} \frac{1}{B_{t+1}} \Omega_{t+1}}_{\text{Indirect Effect}} - \underbrace{F_{t+1} \left[1 - RV_{t+1}^B\right]}_{\text{Default Risk Effect}} \right) \right\},$$

where the term Ω_{t+1} is defined as:

$$\Omega_{t+1} \equiv (B_{t+1} - (1-\chi)\mathcal{P}_{t+1}(\omega_{t+1}^*) + D_{t+1}^I) f(\omega_{t+1}^*) \cdot \frac{d\omega_{t+1}^*}{dB_{t+1}} + F_{t+1} RV_{t+1}^B.$$

The term $-F_{t+1}[1 - RV_{t+1}^B]$ reflects the *direct* reduction in expected default losses when the bailout probability π_{t+1} increases. Higher π_{t+1}, because external intervention is antic-

[2]For the purpose of the analysis I am ignoring the effect of changes in the bailiut probability π_{t+1} of the stochastic discount factor $\mathcal{M}_{t,t+1}$. In the same way, one can prove that intermediaries will alway choose to issue as much deposits as they can so that $D_{t+1}^I = \bar{D}_t$.

ipated, *directly narrows* credit spreads. This component unambiguously contributes a negative value to $\frac{\partial(r_t - r_t^{rf})}{\partial \pi_{t+1}}$. The term $(1-\pi_{t+1})\frac{\partial B_{t+1}}{\partial \pi_{t+1}}\frac{1}{B_{t+1}}\Omega_{t+1}$ captures how increased bailout probabilities π_{t+1} incentivize banks to adjust their debt levels B_{t+1}. If the semi-elasticity of leverage with respect to the bailout probability $\frac{\partial B_{t+1}}{\partial \pi_{t+1}}\frac{1}{B_{t+1}} > 0$ (i.e., banks take on more debt if π_{t+1} increases), the sign of this effect depends on Ω_{t+1}. The first subterm represents increased expected losses from extending the default threshold ω^*_{t+1} as debt rises (positive since $\frac{d\omega^*}{dB_{t+1}} > 0$). The second subterm reflects dilution of recovery values across existing debt (always positive). Hence, upon an increase in π_{t+1}, this channel *widens* spreads, partially offsetting the direct effect. The intuition is that an increase in π_{t+1} incentivizes intermediaries to take on more debt, which in turn increases the probability of default and the credit spread.

Figure 7 shows the generalized impulse response function to a two standard deviations decrease in π_t in the baseline economy and in the case in which intermediaries were not allowed to change their debt in response to the shock. The impulse response starting point is chosen so that debt is in the 99% percentile of its ergodic distribution. I hold the other state variables fixed at their unconditional ergodic mean. The variable reported are the one-period credit spread $r_t - r_t^{rf}$, the risk neutral default probability and the intermediaries debt B^I_{t+1}. A decrease in the bailout probability directly increases credit spreads (*direct effect*) and on impact the solvency risk of intermediaries given the higher cost of funding. A decrease in π_{t+1} however incentivizes intermediaries to de-risk, reduing their debt, which in turn decreases the probability of default and the credit spread (*indirect effect*). The distance between the baseline and fixed-debt paths quantifies the strength of the indirect effect relative to the direct effect. On impact the spread in the fixed-debt case increases by more since now intermediaries cannot adjust their capital structure. Over time the recessionary effect of the shock is also stronger in the fixed-debt almost tripling the recovery rate of the economy.

6 Quantitative Analysis

6.1 Calibration

I now fit the model to US bank level data at the quarterly frequency from 2000 to 2020. For consistency, I use the same sample of banks from which I construct risk-neutral default rates in Section 3. This section presents the data and reports the numerical values of the model's parameters together with the fit of the model. Table 3 lists all parameters, both externally set and calibrated. Table 4 reports the model's moments and their data counterparts. Appendix C provides detailed information on the data sources and variables'

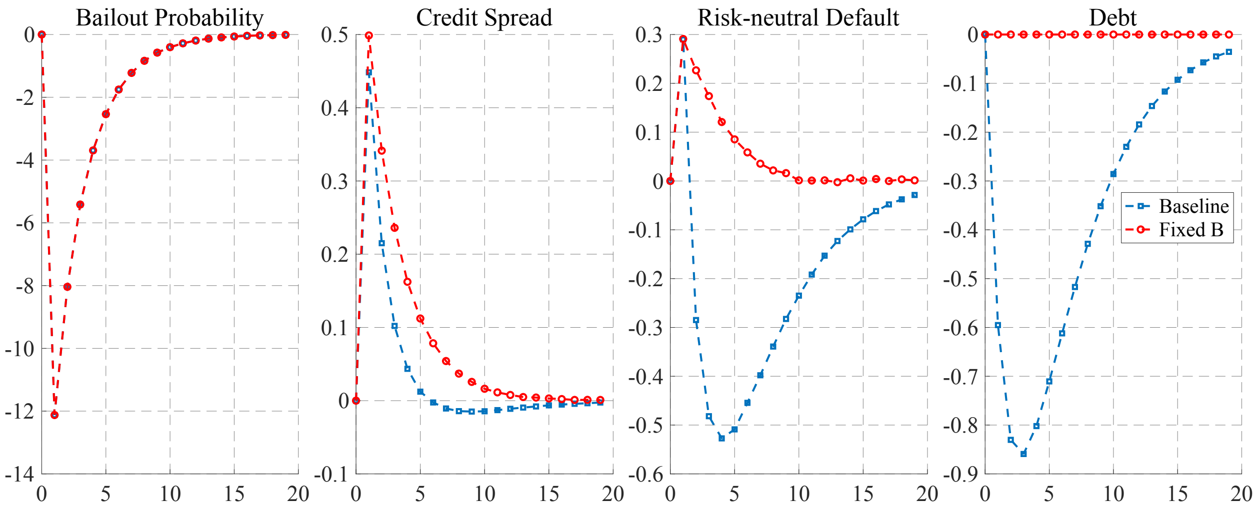


Figure 7: The graphs show the average path of the economy through an increase in π_t by two standard deviations that starts at $t = 1$ (solid blue squares). The dotted red line plots the same shock when debt is held fixed at its ergodic mean. Values are reported as percentade deviations from stationary equilibrium. Each line is the mean of 50,000 Monte-Carlo paths of length 20, all starting from the ergodic state at $t = 0$.

definitions.

The presence of large shocks, substantial risk and occasionally binding constraints, make prices and quantities highly nonlinear functions of the state space. Hence, I solve the model globally using transition function iteration adapted from Elenev et al. (2021) and described in Appendix D. To generate the model moments I run 80,000 years simulations (each with 500 period "burn-in") and report bootstrapped statistics. The model-generated values, unless otherwise specified, are computed from a sample conditional on no disaster realization.

Fundamental risk. All parameters governing fundamental risk are calibrated to match moments of the option-implied Bank of America investment-grade (AAA–BBB) corporate-bond spread. The disaster-arrival probability, π_d, and the conditional survival probability, π_s, are selected to replicate, respectively, the empirical frequency of disaster onsets and the average length of disaster spells. The persistence parameter of the aggregate shock, ρ, is set to match the spread's first-order autocorrelation (0.52 in the data). The innovation volatility, σ^z, targets the unconditional standard deviation of the spread (0.66%). The disaster-severity coefficient, ζ, is chosen so that the model reproduces the mean spread observed during disaster episodes (5.24%). Finally, the loss-severity parameter, η, is calibrated to the bond and loan recovery losses documented by Elenev et al. (2021), ensuring that credit-loss dynamics in the model align with observed corporate default outcomes.

Preferences. The time discount factor affects the mean of the short-term interest rate. I set $\beta = 0.987$ to match the observed average real rate of interest of 1.22% and the intertemporal elasticity of substitution ν to match the volatility of the short-term interest rate measured by the 3-month Treasury bill rate at 2.1%. I set the risk aversion parameter to unity, $\gamma = 7$ to match the weighted average risk neutral variance of equity returns of 8.4% in the data as calculated from equity options data following Martin (2017).

Financial intermediaries. The intermediary borrowing constraint parameter ξ can be interpreted as a minimum regulatory equity capital requirement. I set $\xi = 0.92$ in the baseline calibration, or a 8% equity capital requirement, conforming with the Basel limits. The deposit insurance fee is set to $\kappa = 0.172\%$ following Begenau & Landvoigt (2022) and the convenience yield on deposits α_D to match deposit spreads of 0.32% in the data (Drechsler et al. 2017). The insured deposit limit $\bar{D}$ determines the insured deposit share of liabilties. The model generates a value of 50% versus the data counterpart of 32%. I set the model parameter $\chi = 0.332$ following Bennett et al. (2015). The equity injection parameter n_0 is set to 0.22 to match the observed average market to book value ratio of 1.55%. To determine the dividend target ϕ_0 of banks, I construct time series of dividends, share repurchases, equity issuances, and book equity, aggregating across all publicly-traded banks. Over my sample period, banks paid out an average 2% of their book equity per year as dividends and share repurchases, which is the value I set for ϕ_0. I calibrate the marginal equity issuance cost for intermediaries, $\phi_1 = 7$, using the same data. With this parameter, I target the equity issuance ratio of the financial sector, defined as equity issuances divided by book equity. A higher equity issuance cost makes issuing external equity more expensive, and lowers the equity issuance ratio. Since banks issue equity on average, the equity issunce rate is 0.785% in the data. I set σ^{ω} to target the mean risk neutral default probability of the banking sector as estimated from equity options in Section 3. Finally, μ_{π}, ρ_{π}, σ_{π} are set to match the observed CDS spread mean, AR(1) coefficient and standard deviation of spreads on unsecured debt, respectively.

6.2 Validation

7 Decomposing Credit Spreads

I turn to the main experiment of the paper and measure the importance of bailout expectations before, during and after the Great Financial Crisis. In particular, I integrate the model with quarterly data over 2004:Q1–2015:Q4 to recover the latent bailout-probability process and to decompose observed credit spreads. The model generates the nonlinear

Table 3: Model parameters

Preset parameters					
Target intermediaries dividend	ϕ_0	0.068	Amortization rate	δ	0.932
Capital requirement	ξ	0.92	Intermediaries bankruptcy cost	χ	0.332
Prob. of $d = 1$	π_d	0.055	Prob. of staying in $d = 1$	π_s	0.7
Deposit insurance fee	κ	0.00172	Convenience yield on deposits	α_D	0.005
Deposit rate sensitivity	β_d	0.34	Deposits cap-output correlation	ζ^D	-0.4
St.dev of deposits cap	σ^D	0.0154	AR(1) of deposits cap	ρ^D	0.94
Calibrated parameters					
Household risk aversion	γ	7	Household EIS	ν	2
Household discount factor	β	0.987	Initial equity injection	n_0	0.22
Bank equity issuance cost	ϕ_1	10	St. dev. island risk	σ^ω	0.12
Disaster severity	ζ	0.1	Firm st. dev. idyo. risk	σ^z	0.7
Bailout probability	$\bar{\pi}$	0.87	Deposits cap	$\bar{D}$	0.4
AR(1) of productivity	ρ	0.9	St.dev of productivity	σ	0.05
AR(1) of bailout prob.	ρ_π	0.7	St.dev of bailout prob.	σ_π	0.6
Corporate bankruptcy cost	η	0.60			

Table 4: Empirical targets: data vs. model

Targets	**Data**	**Model**
BofA IG Bond Spread	0.0135	0.0115
BofA IG Bond Spread in $d = 1$	0.0524	0.0210
AR(1) of BofA IG Bond Spread	0.52	0.54
BofA IG Bond Spread volatility	0.0066	0.0051
Corporate Bond & Loan Severities	0.514	0.545
Intermediaries equity payout rate	0.0085	0.0035
Intermediaries market to book value	1.54	1.08
Risk-free rate	0.0122	0.0126
Risk-free rate volatility	0.0210	0.0190
Insured deposits share of liabilities	0.32	0.5
Intermediaries risk neutral variance of equity returns	0.084	0.054
Intermediaries risk neutral default rate	0.0357	0.0479
Credit Default Swap rate	0.0066	0.0055
AR(1) of Credit Default Swap rate	0.23	0.45
Credit Default Swap rate volatility	0.0154	0.0032

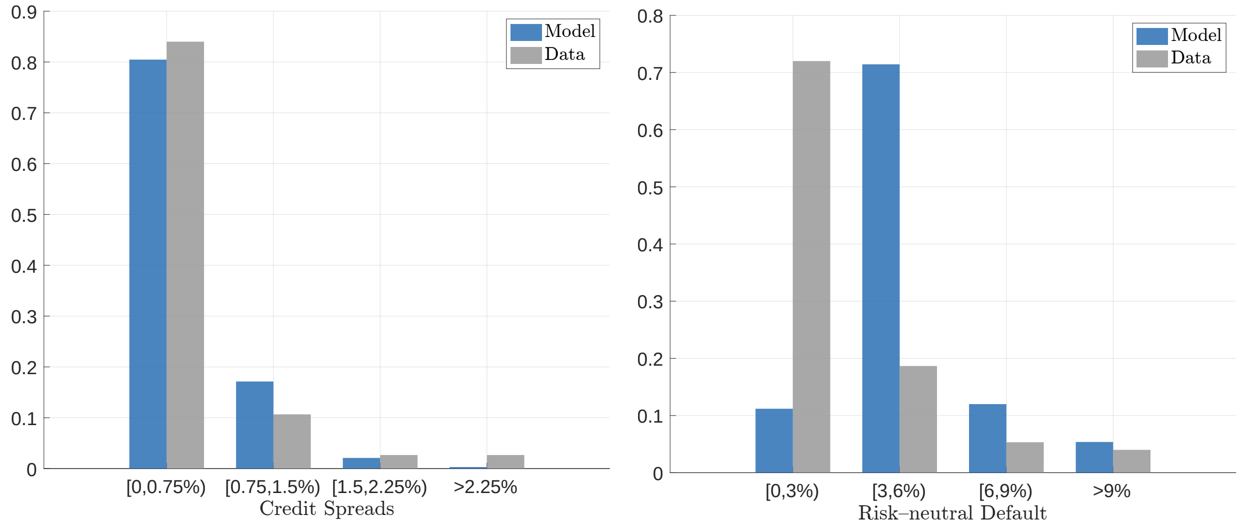


Figure 8: Histograms for model-simulated and empirical moments, 2000–2020. Left: one-year credit spreads (data described in Section 3 and the simulated sample used for Table 4). Right: risk-neutral default probabilities based on the same data and simulation.

state–space system

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{g}\big(\mathbf{S}_t\big) + \boldsymbol{\eta}_t, \\ \mathbf{S}_t &= \mathbf{f}\big(\mathbf{S}_{t-1}, \boldsymbol{\varepsilon}_t\big), \end{aligned} \tag{31}$$

where

$$\mathbf{S}_t = \big[D_t,\ \pi_t,\ Z_t,\ d_t\big]^\top, \qquad \boldsymbol{\varepsilon}_t = \big[\varepsilon_t^D,\ \varepsilon_t^\pi,\ \varepsilon_t^Z,\ \varepsilon_t^d\big]^\top.$$

The vector $\mathbf{Y}_t$ collects the three observables

$$\mathbf{Y}_t = \big[CS_{t,365},\ Q^*_{t,365},\ \Delta D_t\big]^\top,$$

namely the credit spread differential $CS_{t,365} \equiv r_{t,365} - r^{rf}_{t,365}$ and the risk neutral default probability $Q^*_{t,365}$ as I construct in Section 3 and the log change in insured deposits ΔD_t. The mapping $\mathbf{g}(\cdot)$ delivers the model-implied one-year credit spread $g_1(\mathbf{S}_t)$ and risk-neutral default probability $g_2(\mathbf{S}_t)$ and deposit growth $g_3(\mathbf{S}_t)$. Empirically, credit spreads are strictly positive and right-skewed, whereas default probabilities lie on the open unit interval. To respect these distributional features, I model the measurement innovations as *log-normal* and *beta* random variables rather than Gaussian noise:

$$CS^{data}_{t,365} = g_1(\mathbf{S}_t)\,\exp(\eta_t^{CS}), \quad \eta_t^{CS} \sim \mathcal{N}\big(-\tfrac{1}{2}\sigma^2_{CS},\ \sigma^2_{CS}\big),$$

$$Q^{*\,data}_{t,365} = g_2(\mathbf{S}_t) + \eta_t^Q, \quad \eta_t^Q \sim \mathrm{Beta}\big(\alpha_t, \beta_t\big) - \mathbb{E}\big[\mathrm{Beta}(\alpha_t, \beta_t)\big],$$

where the beta parameters (α_t, β_t) are calibrated each period to match the filtered mean $g_2(\mathbf{S}_t)$ and a variance set equal to $0.01\,\widehat{\sigma}^2\big(Q^{*\,data}_{t,365}\big)$. The log-variance σ^2_{CS} is fixed analogously at $0.01\,\widehat{\sigma}^2\big(CS^{data}_{t,365}\big)$. Independent log-normal and beta likelihoods are thus used within the particle filter to update the state vector in each quarter. I set the measurement error of insured deposit growth to 0 so that the model-implied insured deposit growth is equal to the observed insured deposit growth, $g_3(\mathbf{S}_t) = \Delta D_t$.

Given the nonlinear mapping $\mathbf{g}(\cdot)$ implied by the model's global solution, I estimate the latent state path $\{\mathbf{S}_t\}_{t=1}^{T}$ using a fully adaptive particle filter; algorithmic details appear in Appendix E. The filter pins down the entire sequence of fundamental shocks $\{\varepsilon_t\}$—including the bailout-probability shock ε_t^{π}—that is consistent with observed spreads, default probabilities and insured deposit growth.

With the filtered states in hand, I design two counterfactual economies that switch off individual transmission channels while holding the macro-financial environment fixed. The first counterfactual isolates the component of movements in credit spreads that is due to the bailout probability. To do so, I feed the policy functions of the model with the filtered state, with the exception that π_t is set to its highest state π^H for all t in the sample. I label the implied credit spread series from this counterfactual as the fundamental component of credit spreads because, by construction, the one-stepahead probability of a bailout is fixed in every period. The difference between the filtered credit spread and the counterfactual one nets out the impact of bailout expectations. I label this difference the bailout component of credit spreads.

Figure 9 plots the historical one-year credit spread together with its model-based decomposition, the default probabilities, insured deposit growth and the recovered bailout probabilities. The orange area represents the, the full reduction (or increase) attributable to bailout policy while the blue area represents the fundamental component. Importantly, the bailout component contributes 67% of the increase in spreads during the GFC as shown in Table 5. During the crisis, the bailout probabiliy drop from its highest state of 94% to 75% in 2009 remaining low until 2013. The importance of the bailout component is somewhat reduced from 2010 to 2012 accounting for around 50% and even more so from 2012 to 2015 accounting for around 32%.

A behavioural story can also explain the wide credit spreads after the GFC. Before the crisis, many creditors did not truly believe that banks could fail (Gennaioli & Shleifer 2018). When Lehman Brothers collapsed—and several other giants nearly followed—creditors suddenly recognised a failure risk that had been present all along but badly under-estimated. The jump in spreads would then reflect a higher perceived chance of insolvency, not a change in expected bailout support. Experienced creditors already knew their claims likely enjoyed some government back-stop, yet the realisation that default was possible still drove spreads up. However, the persistence of those wider spreads implies that the post-Lehman shift in perceived failure risk lasted for years. This was not the case, as we can see from the default probabilities in Figure 9, which quickly moved back toward pre-crisis levels.

Table 5: Bailout component and contribution of endogenous leverage as a percentage of model implied credit spreads across sub-periods.

	2008–2010	**2010–2012**	**2012–2015**
$\pi_t = \pi^H$ (%)	67.03	49.53	31.82
$B_{t+1} = \bar{B}$ (%)	-45.25	-39.54	-4.034

As bailout probabilities and fundamentals evolve, so does intermediaries' capital structure. While previous work treated the banking sector's capital structure as fixed exogenous, the following counterfactual demonstrates the importance of accounting for intermediaries' endogenous response to changes in fundamentals and bailout probabilities. I conduct the same exercise while holding intermediaries' debt position fixed at its ergodic mean $\bar{B}$, allowing bailout expectations to evolve freely. The resulting spread is depicted by the green dotted-dashed line in Figure 10, alongside the baseline model-implied spread and the counterfactual spread with fixed bailout policy. The right panel displays the model's debt (blue-dashed) and its data counterpart (black solid). During the pre-crisis period (2004–2006), the green and blue lines nearly overlap. This indicates that when fundamentals are calm or bailout perceptions high, leverage adjustment is negligible, as intermediaries exploit low debt costs to increase leverage. In 2007–2009, the baseline spread surges to roughly 150 bp, while the orange series rises only about half as much. This divergence provides evidence that investors demand a sizable bailout premium when public support appears less certain. Conversely, the green line *overshoots* the baseline, revealing how banks' endogenous deleveraging cushions part of the bailout-driven widening. As Table 5 illustrates, this counterfactual spread reaches 40% of the baseline spread during the crisis and remains elevated until 2012. The right panel traces the corresponding debt growth in the baseline economy (blue-dashed) and the data (black solid). The baseline shows deleveraging of about 15% through 2009, followed by a gradual rebuild that closely resembles the data. Because the green line systematically overpredicts spreads relative to the baseline during crises, any model ignoring banks' balance-sheet response could only fit the data by *dialing down the estimated bailout probability*. This misspecification consequently leads to an *underestimation* of the bailout component in credit spreads–even though government guarantees are the true driver of the observed swings.

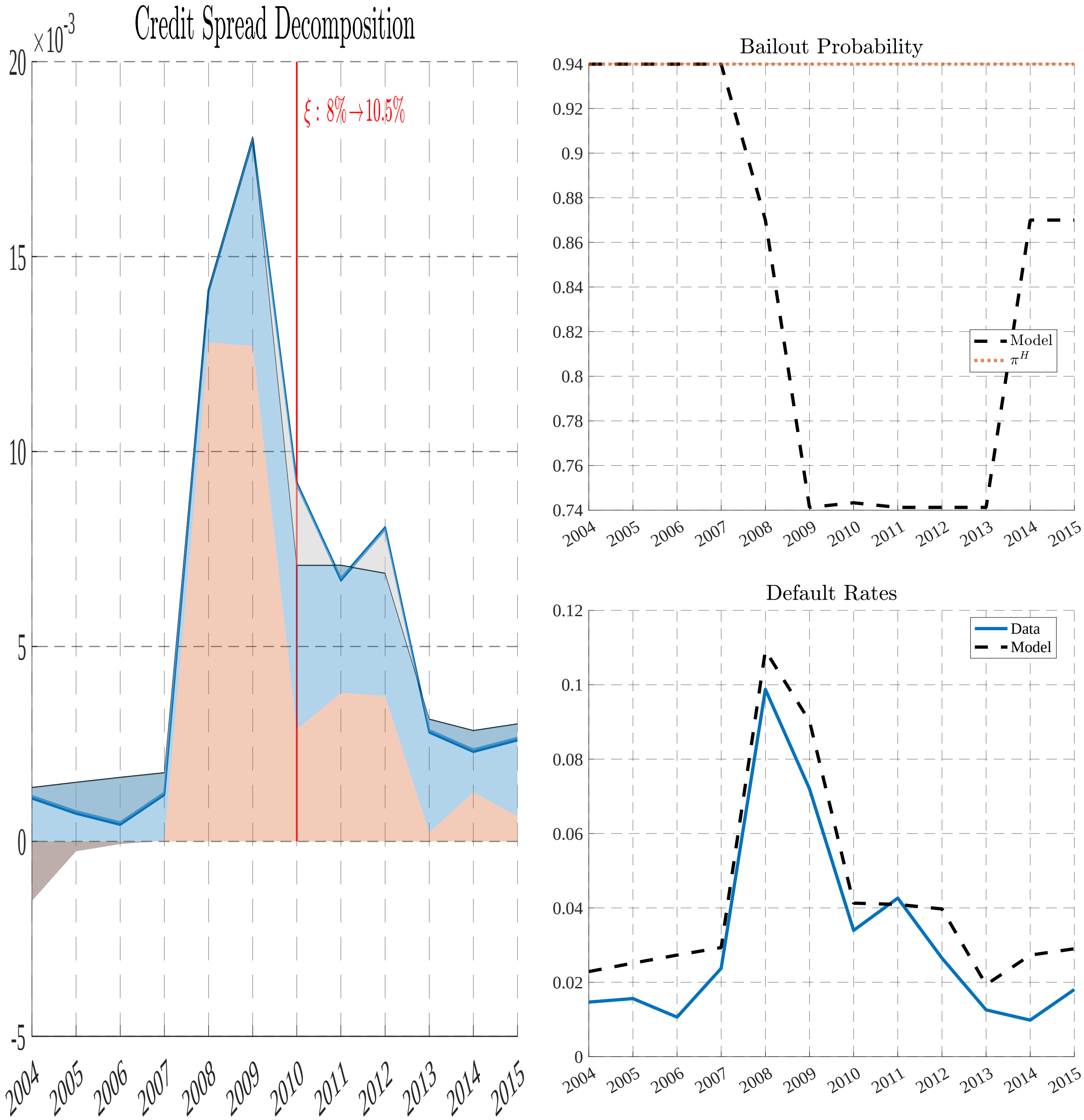


Figure 9: Annual median one-year credit spread and its model decomposition (*left*), implied bailout probability (*top-right*), and default probabilities (*bottom-right*).

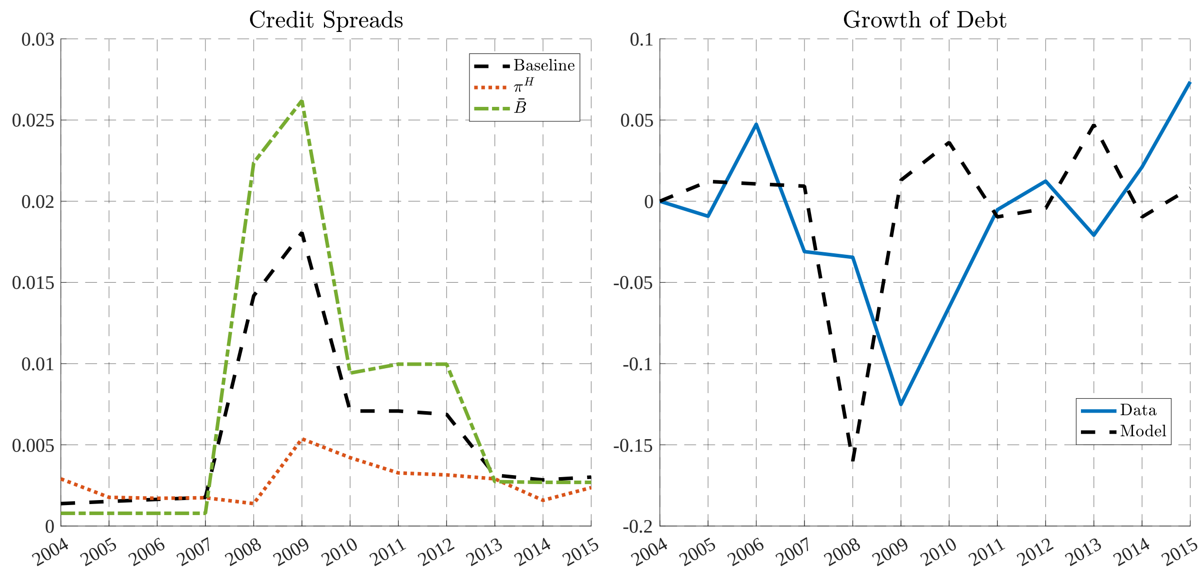


Figure 10: Left: model spread (black dashed), counterfactual with $\pi_t = \pi^H$ (orange dotted), and counterfactual with $B_{t+1} = \bar{B}$ (green dash–dot). Right: model debt growth (black dashed) versus the data counterpart (blue solid).

8 Bailouts, Regulation and Risk Exposures

This section develops the quantitative bridge between post-crisis policy shifts and banks' balance-sheet risk. I (i) construct an *asset-return factor* that summarises unexpected fluctuations in loan-portfolio pay-offs, (ii) estimate the equity loading β_{AR} on that factor, and (iii) use counter-factual exercises to isolate how smaller bailout probabilities and tighter capital requirements feed through to funding spreads, asset valuations, and the prices of aggregate and jump risk.

Define the ex-dividend equity price as Q_t. Holding this equity from t to t+1 delivers the gross return

$$R_{I,t+1} = \frac{1}{Q_t} \frac{V(n_{t+1}; \mathbf{S}_{t+1})}{n_{t+1}} \left[1 - F_{t+1}(\omega^*_{t+1})\right] \left(\mathcal{P}_{t+1}(\omega^+_{t+1})\, \tilde{a}_{t+1} - \tilde{b}^I_{t+1} - \tilde{d}^I_{t+1}\right), \tag{32}$$

and the expected return is $\mathbb{E}_t[R_{I,t+1}]$. The asset-return factor against which exposure is measured is constructed as the difference $R_{A,t+1} - \mathbb{E}_t[R_{A,t+1}]$, where $R_{A,t+1}$ is constructed from the first order condition of the intermediary's problem for the asset portfolio in (29). The loading of equity returns on the asset-return factor is

$$\beta_{AR} = \frac{\mathrm{Cov}\left(R_{I,t+1} - \mathbb{E}_t[R_{I,t+1}], f_{t+1}\right)}{\mathrm{Var}\left(f_{t+1}\right)}. \tag{33}$$

β_{AR} is the slope coefficient of the no-intercept regression

$$R_{I,t+1} - \mathbb{E}_t[R_{I,t+1}] \;=\; \beta_{AR}\left(R_{A,t+1} - \mathbb{E}_t[R_{A,t+1}]\right) + \varepsilon_{t+1}, \qquad \mathbb{E}\big[\left(R_{A,t+1} - \mathbb{E}_t[R_{A,t+1}]\right)\varepsilon_{t+1}\big] = 0.$$

The regression gauges how strongly intermediary equity co-moves with unexpected fluctuations in the payoff of the underlying loan portfolio, abstracting from movements in the stochastic discount factor. When bailout probabilities fall, a larger share of bad-state losses is absorbed by equity and by the assets themselves, raising their covariance more than the variance of the asset return and thereby increasing β_{AR}. The statistic thus summarises the internal risk transfer between the loan portfolio and equity.

But how does the intermediary prices the risks embedded in his asset portfolio? The intermediary faces two systematic shocks: an aggregate productivity innovation Z_{t+1}, modelled as a mean-zero AR(1) error, and a rare disaster shock d_{t+1} that raises default losses in extreme states. Let $f_{t+1} = (Z_{t+1}, d_{t+1})^\top$ collect the two factors. The intermediary's stochastic discount factor is

$$\mathcal{M}^I_{t+1} \;=\; \frac{\mathcal{M}_{t,t+1}}{1 - \lambda_t\,\xi}\,\tilde{v}(S_t)\,,$$

where $\mathcal{M}_{t,t+1}$ is the household SDF, $\tilde{v}(S_t)$ is the marginal value of one additional unit of intermediary net worth, λ_t is the Lagrange multiplier on the leverage constraint, and ξ the haircut parameter in that constraint. Any payoff R_{t+1} must satisfy the Euler equation $\mathbb{E}[\mathcal{M}^I_{t+1}R_{t+1}] = 1$, so the shadow risk-free gross rate implied by the intermediary is $r^I_f = 1/\mathbb{E}[\mathcal{M}^I_{t+1}]$, typically above the observable Treasury rate $r_f = 1/\mathbb{E}[\mathcal{M}_{t,t+1}]$ because the intermediary puts extra weight on stress states. For each factor $f \in \{Z, d\}$ the price of risk, defined as the expected excess return on a portfolio with unit beta to f and zero beta to the other factor, is

$$\lambda_f \;=\; -\frac{\mathrm{Cov}\big(\mathcal{M}^I_{t+1}, f_{t+1}\big)}{\mathbb{E}[\mathcal{M}^I_{t+1}]}, \qquad f \in \{Z, d\}.$$

Hence for any traded return R_{t+1} with factor betas β_Z and β_d the model delivers a two-factor securities–market line

$$\mathbb{E}[R_{t+1}] - r^I_f \;=\; \lambda_Z\,\beta_Z + \lambda_d\,\beta_d.$$

Table 6 quantifies the contribution of the post-crisis fall in the perceived bailout probability and tighter capital requirements to banks' funding costs and asset prices. Relative to the pre-2008 benchmark the average unsecured spread paid after 2010 rises by 34 basis points in the baseline model, yet by only 8.8 basis points when the high pre-crisis bailout probability (π^H) is kept in place. The difference of roughly 25.5 basis points—almost

	Baseline	π^H	ξ
Spread (bp)	34.32	8.83	22.10
Asset price (%)	-5.35	-2.17	-3.10
Exposure (%)	29.23	-4.08	18.50
r_t^I (bp)	273	-13	110
Price of *normal* risk (bp)	1.32	-0.18	0.1
Price of *disaster* risk (bp)	12.17	8.87	10.20

Table 6: Pre-2008 vs. post-2010 comparison of baseline and counter-factual economies. Column π^H retains the pre-crisis bailout probabilities; column ξ retains the pre-crisis capital requirement.

three quarters of the observed increase—can therefore be attributed directly to the reassessment of government support. Put differently, debt would have remained almost four times cheaper had investors continued to believe in large-scale bailouts. Tighter capital requirments post-2010, by reducing the leverage in the banking system and so its insolvency risk, contributed to keep spread lower by around 10bp.

The same comparison explains most of the persistent weakness in asset prices. In the baseline the representative loan-portfolio price is 5.35 percent below its pre-2008 average, whereas under the π^H counterfactual it is only 2.17 percent lower. Hence a drop of about 3.2 percentage points, or sixty per cent of the total decline, stems from diminished bailout expectations. Figure 11 corroborates this result: the baseline path plunges more deeply during the 2008–09 turmoil and never fully closes the gap, while the counterfactual path rebounds to near-pre-crisis levels by 2012.

Balance-sheet exposure behaves in the opposite direction. After 2010 the baseline economy exhibits a 29.2 percent increase in measured exposure, whereas the π^H scenario shows a slight decline of 4.1 percent. The resulting gap of more than 33 percentage points implies that the upward shift in risk taking is entirely driven by lower bailout expectations.

Moving to the pricing of risks, a lower government bail-out probability raises the cost of capital only conditional to disaster states, strongly increasing $\mathrm{Cov}(\mathcal{M}_{t+1}^I, d_{t+1})$ and therefore λ_d, while leaving λ_Z almost unchanged, compared to changes in the capital requirement. A tighter capital requirement lifts the cost of capital uniformly across states, and pushing *both* covariances—and thus both λ_Z and λ_d—upward in roughly equal proportion. In short, weaker public guarantees tilt the securities–market line mainly along the disaster dimension, whereas stricter regulation shifts the intercept r_f^I and raises its slope in every direction. Because the units of each λ_x are exactly those of an excess gross return per period, the resulting changes can be read as the additional premium investors demand for bearing an extra unit of aggregate or disaster beta after the policy interven-

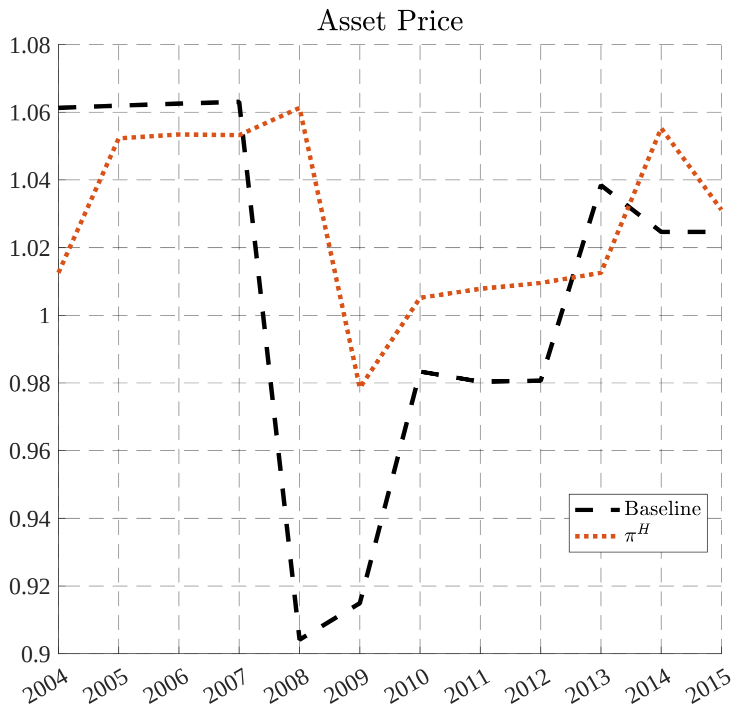


Figure 11: Asset price (black dashed) and the counterfactual with $\pi_{t+1} = \pi^H$ (orange dotted).

tion. This distinction—*state-contingent* versus *state-independent* funding stress—explains why the two policies leave different fingerprints on the observed securities-market line.

Taken together, the numbers show that the post-crisis *repricing of government guarantees* is the dominant driver of higher funding costs, weaker asset valuations, and the dramatic reallocation of intermediary portfolios away from jump-risk-intensive assets, which could be explained alone by tighter capital requirements.

9 Conclusion

References

Adrian, T. & Boyarchenko, N. (2012), 'Intermediary leverage cycles and financial stability', *Becker Friedman Institute for Research in Economics Working Paper* (2012-010). 4

Atkeson, A. G., d'Avernas, A., Eisfeldt, A. L. & Weill, P.-O. (2019), 'Government guarantees and the valuation of american banks', *NBER Macroeconomics Annual* **33**(1), 81–145. 4

Begenau, J. (2020), 'Capital requirements, risk choice, and liquidity provision in a business-cycle model', *Journal of Financial Economics* **136**(2), 355–378. 4

Begenau, J. & Landvoigt, T. (2022), 'Financial regulation in a quantitative model of the modern banking system', *The Review of Economic Studies* **89**(4), 1748–1784. 30

Bennett, R. L., Güntay, L. & Unal, H. (2015), 'Inside debt, bank default risk, and performance during the crisis', *Journal of Financial Intermediation* **24**(4), 487–513. 30

Berndt, A., Duffie, D. & Zhu, Y. (2022), 'The decline of too big to fail', *Available at SSRN 3497897* . 1, 4, 12

Brunnermeier, M. K. & Sannikov, Y. (2014), 'A macroeconomic model with a financial sector', *American Economic Review* **104**(2), 379–421. 4, 60

Carr, P. & Wu, L. (2011), 'A simple robust link between american puts and credit protection', *The Review of Financial Studies* **24**(2), 473–505. 1, 4, 7

Chari, V. V. & Kehoe, P. J. (2016), 'Bailouts, time inconsistency, and optimal regulation: A macroeconomic view', *American Economic Review* **106**(9), 2458–2493. 1, 4

Conrad, J., Dittmar, R. F. & Hameed, A. (2020), 'Implied default probabilities and losses given default from option prices', *Journal of Financial Econometrics* **18**(3), 629–652. 14

Corbae, D. & D'Erasmo, P. (2019), Capital requirements in a quantitative model of banking industry dynamics, Technical report, National Bureau of Economic Research. 4

Dávila, E. & Walther, A. (2023), 'Prudential policy with distorted beliefs', *American Economic Review* **113**(7), 1967–2006. 67

DeMarzo, P. M., Krishnamurthy, A. & Nagel, S. (2024), Interest rate risk in banking, Technical report, National Bureau of Economic Research. 22

Dovis, A. & Kirpalani, R. (2022), 'Reputation, bailouts, and interest rate spread dynamics', *American Economic Journal: Macroeconomics* **14**(3), 411–449. 4

Drechsler, I., Savov, A. & Schnabl, P. (2017), 'The deposits channel of monetary policy', *The Quarterly Journal of Economics* **132**(4), 1819–1876. 22, 30

Elenev, V., Landvoigt, T. & Van Nieuwerburgh, S. (2021), 'A macroeconomic model with financially constrained producers and intermediaries', *Econometrica* **89**(3), 1361–1418. 4, 29, 51, 60

Farhi, E. & Tirole, J. (2012), 'Collective moral hazard, maturity mismatch, and systemic bailouts', *American Economic Review* **102**(1), 60–93. 4

Gandhi, P. & Lustig, H. (2015), 'Size anomalies in us bank stock returns', *The Journal of Finance* **70**(2), 733–768. 4

Gandhi, P., Lustig, H. & Plazzi, A. (2020), 'Equity is cheap for large financial institutions', *The Review of Financial Studies* **33**(9), 4231–4271. 4

Garleanu, N. & Pedersen, L. H. (2011), 'Margin-based asset pricing and deviations from the law of one price', *The Review of Financial Studies* **24**(6), 1980–2022. 4

Gennaioli, N. & Shleifer, A. (2018), 'A crisis of beliefs: Investor psychology and financial fragility'. 33

Haddad, V., Moreira, A. & Muir, T. (2023), Whatever it takes? the impact of conditional policy promises, Technical report, National Bureau of Economic Research. 4

He, Z. & Krishnamurthy, A. (2013), 'Intermediary asset pricing', *American Economic Review* **103**(2), 732–770. 4

Hett, F. & Schmidt, A. (2017), 'Bank rescues and bailout expectations: The erosion of market discipline during the financial crisis', *Journal of Financial Economics* **126**(3), 635–651. 4

Jiang, E. X., Matvos, G., Piskorski, T. & Seru, A. (2024), 'Monetary tightening and us bank fragility in 2023: Mark-to-market losses and uninsured depositor runs?', *Journal of Financial Economics* **159**, 103899. 22

Kareken, J. H. & Wallace, N. (1978), 'Deposit insurance and bank regulation: A partial-equilibrium exposition', *Journal of business* pp. 413–438. 1, 3, 4

Kelly, B., Lustig, H. & Van Nieuwerburgh, S. (2016), 'Too-systemic-to-fail: What option markets imply about sector-wide government guarantees', *American Economic Review* **106**(6), 1278–1319. 4

Krishnamurthy, A. & Muir, T. (2017), How credit cycles across a financial crisis, Technical report, National Bureau of Economic Research. 4

Martin, I. (2017), 'What is the expected return on the market?', *The Quarterly Journal of Economics* **132**(1), 367–433. 30

Mendicino, C., Nikolov, K., Rubio-Ramírez, J. F., Suarez, J. & Supera, D. (2019), 'Twin defaults and bank capital requirements', *Available at SSRN 3536486* . 4, 18

Minton, B. A., Stulz, R. M. & Taboada, A. G. (2019), 'Are the largest banks valued more highly?', *The Review of Financial Studies* **32**(12), 4604–4652. 4

Nagel, S. (2012), 'Evaporating liquidity', *The Review of Financial Studies* **25**(7), 2005–2039. 14

Nagel, S. & Purnanandam, A. (2020), 'Banks' risk dynamics and distance to default', *The Review of Financial Studies* **33**(6), 2421–2467. 18

Panageas, S. (2010), 'Bailouts, the incentive to manage risk, and financial crises', *Journal of Financial Economics* **95**(3), 296–311. 4

Rouwenhurst, K. (1995), 'Asset pricing implication of real business cycle models', *Frontiers of Business Cycle Research, Thomas Cooley editor, Princeton University Press* . 51

Schweikhard, F. A. & Tsesmelidakis, Z. (2011), The impact of government interventions on cds and equity markets, *in* 'Finance Meeting EUROFIDAI-AFFI, Paris, December'. 4

Van den Heuvel, S. J. (2008), 'The welfare cost of bank capital requirements', *Journal of Monetary Economics* **55**(2), 298–320. 4

Veronesi, P. & Zingales, L. (2010), 'Paulson's gift', *Journal of Financial Economics* **97**(3), 339–368. 4

A Robustness

A.1 Alternative Estimator for Risk Neutral Default Probabilities

An alternative method to estimate the default region relies on the Theil–Sen estimator rather than ordinary least squares (OLS). Specifically, I preserve the progressive window expansion framework, beginning with the two lowest strikes $\{K_1, K_2\}$ and incrementally increasing the candidate window size m from 2 to n. For each time t, maturity T and proposed window $\{K_1, \dots, K_m\}$, the Theil–Sen slope estimate is given by

$$\hat{\beta}_{TS} \;=\; \text{median}_{1 \leqslant i < j \leqslant m} \left\{ \frac{\text{Put}(K_j) - \text{Put}(K_i)}{K_j - K_i} \right\}.$$

Once $\hat{\beta}_{TS}$ is obtained, the modified coefficient of determination through the origin,

$$R^2 \;=\; 1 \;-\; \frac{\sum_{i=1}^{m} \left(\text{Put}(K_i) - \hat{\beta}_{TS}\, K_i\right)^2}{\sum_{i=1}^{m} \text{Put}(K_i)^2},$$

is computed to evaluate the goodness-of-fit. As long as R^2 exceeds a predefined threshold $\tau = 0.98$, the procedure allows the window size m to expand. The iteration terminates when adding an additional strike K_{m+1} causes R^2 to drop below τ. Denoting by m^* the largest m for which the threshold requirement holds, I identify the upper boundary of the default region as $\mathcal{E} = K_{m^*}$. Finally, within this region of strikes $\{K_1, \dots, K_{m^*}\}$, the Theil–Sen slope

$$\hat{\beta}_{TS} \;=\; \text{median}_{1 \leqslant i < j \leqslant m^*} \left\{ \frac{\text{Put}(K_j) - \text{Put}(K_i)}{K_j - K_i} \right\}$$

serves as the estimate of the risk-neutral default probability. The average estimate for maturity of 35 days is reported in Figure A.1. The time series looks very similar to the one obtained using OLS in Figure 4a.

A.2 The Variation in Credit Spreads Explained by Expected Losses

To assess the degree to which variation in credit spreads mirrors changes in expected losses I estimate

$$\log\bigl(CS_{i,t,365}\bigr) = \beta_0 + \beta_1 \log\bigl(LGD^*_{i,t,365}\bigr) + \sum_i \beta^i D^i + \sum_t \beta^t D^t + \varepsilon_{i,t}, \qquad \text{(A.1)}$$

where $CS_{i,t,365}$ denotes the one-year CDS spread and $LGD^*_{i,t,365}$ the corresponding risk-neutral expected loss at time t for bank i. Equation (A.1) is estimated under four sets of

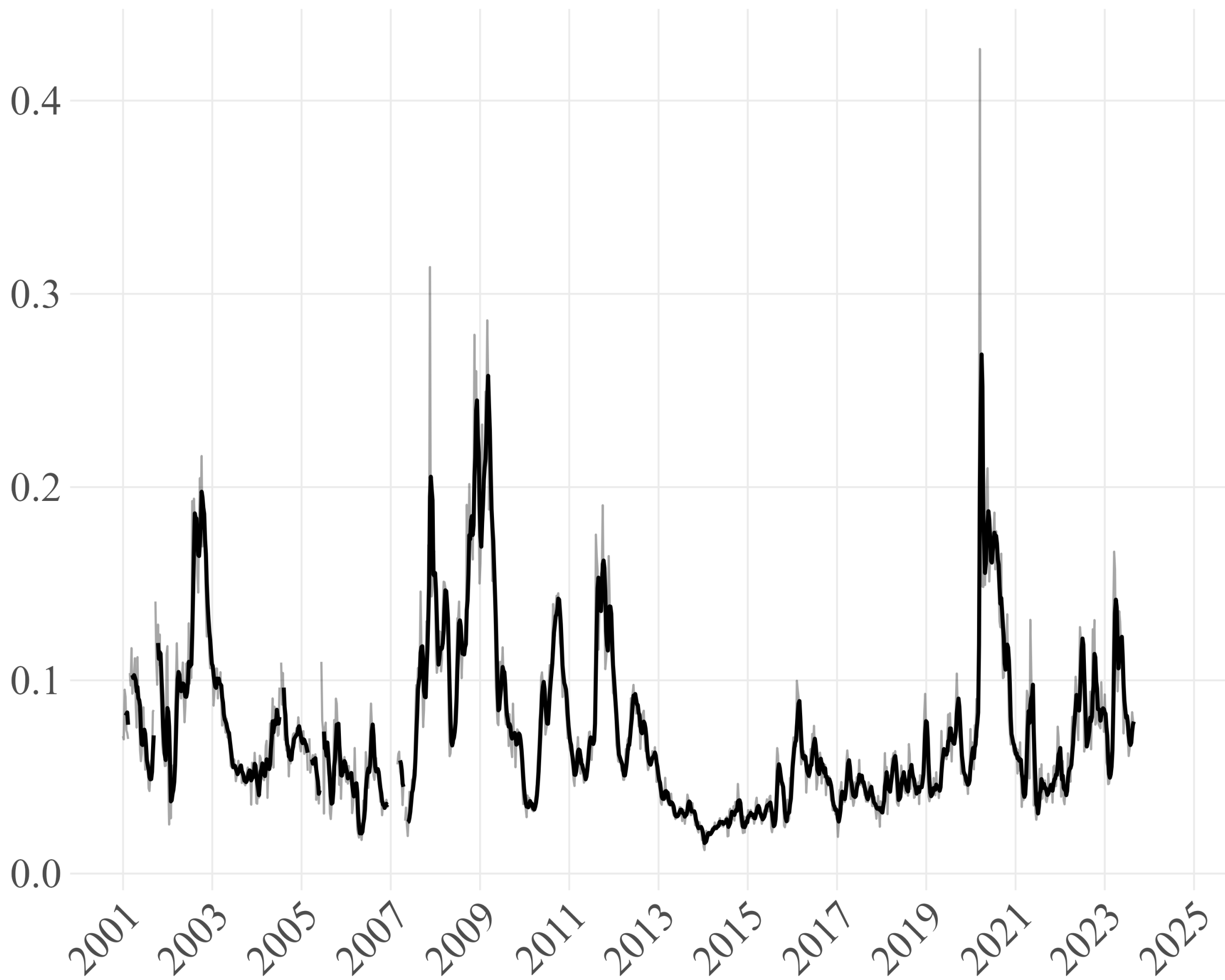


Figure A.1: Average $\mathbb{Q}^{*}_{t,T}$ for $T = 365$ using the Theil–Sen estimator.

fixed effects. Table A.1 summarises the results.

Across all four specifications the elasticity of one-year CDS spreads to expected losses is strictly below one and highly significant. In the two-way fixed-effects model the coefficient on $\log(\mathrm{LGD}^*_{t,365})$ equals 0.710 with a clustered standard error of 0.066, so the null hypothesis of unit elasticity is rejected at the one-percent level. Under risk-neutral valuation spreads would move one-for-one with expected losses; a coefficient below unity therefore points to a positive price of default risk, as investors demand an additional premium that attenuates the mechanical pass-through from losses to spreads once bank and date heterogeneity are purged.

The overall coefficient of determination R^2 rises monotonically with the inclusion of fixed effects and reaches 0.936 in the full model, indicating that cross-sectional and temporal dummies absorb nearly all variation in levels. The within-bank R^2 climbs from 0.327 when only bank effects are added to 0.700 with date effects alone, then settles at 0.583 in the two-way specification. These fit statistics show that expected losses remain the primary driver of time-series variation in spreads after accounting for extensive heterogeneity, yet investor risk aversion still drags the elasticity markedly below the theoretical benchmark of one.

Dependent Variable:	$\log(\mathrm{CS}_{t,365})$			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-3.813***			
	(0.1672)			
$\log(\mathrm{LGD}^*_{t,365})$	0.9022***	0.7393***	0.8514***	0.7104***
	(0.0632)	(0.0585)	(0.0721)	(0.0657)
Fixed-effects				
bank		Yes		Yes
date			Yes	Yes
Fit statistics				
Observations	33,959	33,959	33,959	33,959
R^2	0.52604	0.61912	0.86919	0.93560
Within R^2		0.32672	0.69964	0.58284

Clustered (bank) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.1: The table reports the results of the panel data regression (A.1). The coefficients β^i and β^t capture bank and day-fixed effects (FEs). Credit spreads and expected recoveries are measured in decimals.

B Agents optimization

Let $\mathbf{S}_t = (d_t, Z_t, \pi_t)$ be the vector of exogenous aggregate state variables.

B.1 Household

The representative household solves

$$V_t(W_t; \mathbf{S}_t) = \max_{C_t, B^H_{t+1}} \left\{ (1-\beta)\, C_t^{1-\frac{1}{\nu}} + \beta\, \mathbb{E}_t\!\left[V_{t+1}^{1-\sigma} \right]^{\frac{1-\frac{1}{\nu}}{1-\sigma}} \right\}^{\frac{1}{1-\frac{1}{\nu}}},$$

subject to

$$W_t - T_t \geqslant C_t + q_t\, B^H_{t+1} + q^d_t\, D^H_{t+1}, \tag{B.1}$$

$$W_t = \Pi_t + \Pi^{div}_t + D^H_t + B^H_t \Big[1 - F_t + F_t\big(\pi + (1-\pi) RV^B_t\big) \Big], \tag{B.2}$$

$$\mathbf{S}_{t+1} = \Gamma\big(\mathbf{S}_t\big). \tag{B.3}$$

Here $F_t \equiv \int_{\omega \in \mathcal{D}_t} dF(\omega)$ is the default probability and RV^B_t the expected recovery value of the bank's bond conditional on default. The certainty equivalent of future utility is

$$CE_t \;=\; \mathbb{E}_t\!\left[V_{t+1}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \qquad \mathcal{M}_{t,t+1} = \beta \left(\frac{V_{t+1}}{CE_t}\right)^{\frac{1}{\nu}-\sigma} \left(\frac{u_{t+1}}{u_t}\right)^{1-\frac{1}{\nu}} \left(\frac{C_{t+1}}{C_t}\right)^{-1}.$$

Taking first–order conditions with respect to bonds yields

$$q_t = \mathbb{E}_t\!\Big[\mathcal{M}_{t,t+1} \left\{ 1 - F_{t+1} + F_{t+1}\big(\pi + (1-\pi) RV^B_{t+1}\big) \right\} \Big], \tag{B.4}$$

Equation (B.4) fully characterise the household's optimal bond choice.

B.2 Intermediaries

B.2.1 Aggregation

Given my assumed functional form for the equity issuance and deposit adjustment costs, the intermediary problem is homogeneous of degree 1 in net worth n_t. I can thus define the scaled variables $\tilde{e}_t = e_t/n_t$, $\tilde{a}_{t+1} = a_{t+1}/n_t$, $\tilde{d}^I_{t+1} = d^I_{t+1}/n_t$, $\tilde{b}^I_{t+1} = b_{t+1}/n_t$, and the value function $\nu\left(\mathbf{S}_t\right)$ such that

$$V\left(n_t, \mathbf{S}_t\right) = n_t \nu\left(\mathbf{S}_t\right).$$

I can write the growth rate of net worth, $\tilde{n}_t = n_t / n_{t-1}$, for some realization of the idiosyncratic shock ω_t and given assets and liabilities $\left(\tilde{a}_t, \tilde{d}_t^I, \tilde{b}_t^I\right)$ as

$$\tilde{n}\left(\omega_t, \tilde{a}_t^I, \tilde{b}_t^I, \tilde{d}_t^I, \mathbf{S}_t\right) = \mathcal{P}_t(\omega_t)\tilde{a}_t - \tilde{b}_t^I - \tilde{d}_t^I. \tag{B.5}$$

Thus, the growth rate next period, conditional on not defaulting, is

$$E_{\omega,t+1}\left[\tilde{n}\left(\omega_{t+1}, \tilde{a}_{t+1}, \tilde{b}_{t+1}^I, \tilde{d}_{t+1}^I, \mathbf{S}_{t+1}\right) \mid \omega_{t+1} > \omega_{t+1}^*\right] = \tilde{n}\left(\omega_{t+1}^+, \tilde{a}_{t+1}, \tilde{b}_{t+1}^I, \tilde{d}_{t+1}^I, \mathbf{S}_{t+1}\right),$$

where

$$\omega_{t+1}^+ = E_{\omega,t+1}\left[\omega \mid \omega > \omega_{t+1}^*\right].$$

Using the definition of $n\left(\omega_t, \tilde{a}_t^I, \tilde{b}_t^I, \tilde{d}_t^I, \mathbf{S}_t\right)$ in (B.5), I can write the representative intermediary problem as

$$\begin{aligned} v\left(\mathbf{S}_t\right) = \max_{\tilde{e}_t, \tilde{a}_{t+1}^I, \tilde{d}_{t+1}^I \leqslant \bar{D}, \tilde{b}_{t+1}^I} \; & \phi_0 - \tilde{e}_t - \frac{\phi_1}{2}\left(\tilde{e}_t\right)^2 \\ & + E_t\left[\mathcal{M}_{t,t+1} v\left(\mathbf{S}_{t+1}\right)\left(1 - F\left(\omega_{t+1}^*\right)\right) \tilde{n}\left(\omega_{t+1}^+, \tilde{a}_{t+1}^I, \tilde{b}_{t+1}^I, \tilde{d}_{t+1}^I, \mathbf{S}_{t+1}\right)\right] \end{aligned} \tag{B.6}$$

subject to

$$1 - \phi_0 + \tilde{e}_t = p_t \tilde{a}_{t+1} - q\left(\tilde{a}_{t+1}, \tilde{b}_{t+1}^I, \tilde{d}_{t+1}^I; \mathbf{S}_t\right)\tilde{b}_{t+1}^I - (q_t^d - \kappa)\tilde{d}_{t+1}^I,$$

and

$$\tilde{b}_{t+1}^I + \tilde{d}_{t+1}^I \leqslant \xi p_t \tilde{a}_{t+1}.$$

B.2.2 First-order conditions

I denote the Lagrange multiplier on the budget constraint by μ_t, the Lagrange multiplier on the leverage constraint by λ_t, and the Lagrange multiplier on the deposit constraint by λ_t^d. The FOC with respect to $\tilde{e}_t$ is

$$\mu_t = 1 + \phi_1 \tilde{e}_t. \tag{B.7}$$

The FOC with respect to a_{t+1} is given by

$$\mu_t\left(p_t - \frac{\partial q_t}{\partial \tilde{a}_{t+1}}\tilde{b}_{t+1}^I\right) = \lambda_t \xi p_t + \mathbb{E}_t\{\mathcal{M}_{t,t+1} v\left(\mathbf{S}_{t+1}\right)(1 - F_{t+1})\mathcal{P}_{t+1}\left(\omega_{t+1}^+\right)\}. \tag{B.8}$$

The FOC for d^I_{t+1} is

$$\mu_t \left(q^d_t - \kappa + \frac{\partial q_t}{\partial \tilde{d}^I_{t+1}} \tilde{b}^I_{t+1} \right) = \lambda_t + \lambda^d_t + \mathbb{E}_t\{\mathcal{M}_{t,t+1} \nu\left(\mathbf{S}_{t+1}\right)\left(1 - F_{t+1}\right)\}. \tag{B.9}$$

Finally, the FOC for b^I_{t+1} yields

$$\mu_t \left(q_t + \frac{\partial q_t}{\partial \tilde{b}^I_{t+1}} \tilde{b}^I_{t+1} \right) = \lambda_t + \mathbb{E}_t\{\mathcal{M}_{t,t+1} \nu\left(\mathbf{S}_{t+1}\right)\left(1 - F_{t+1}\right)\}. \tag{B.10}$$

The envelope condition is

$$\nu\left(\mathbf{S}_t\right) = \phi_0 + \frac{\phi_1}{2} \tilde{e}^2_t + \mu_t\left(1 - \phi_0\right).$$

I can divide by μ_t and re-write more compactly

$$p_t - \frac{\partial q_t}{\partial \tilde{a}^I_{t+1}} \tilde{b}^I_{t+1} - \tilde{\lambda}_t \xi p_t = \mathbb{E}_t\{\mathcal{M}^I_{t+1} \mathcal{P}_{t+1}(\omega^+_{t+1})\}, \tag{B.11}$$

$$q^d_t - \kappa + \frac{\partial q_t}{\partial \tilde{d}^I_{t+1}} \tilde{b}^I_{t+1} - \tilde{\lambda}_t - \tilde{\lambda}^d_t = \mathbb{E}_t\{\mathcal{M}^I_{t+1}\}, \tag{B.12}$$

$$q_t + \frac{\partial q_t}{\partial \tilde{b}^I_{t+1}} \tilde{b}^I_{t+1} - \tilde{\lambda}_t = \mathbb{E}_t\{\mathcal{M}^I_{t+1}\}. \tag{B.13}$$

where I define the SDF of the intermediaries $\mathcal{M}^I_{t+1}$ as

$$\mathcal{M}^I_{t+1} = \mathcal{M}_{t,t+1} \frac{\nu\left(\mathbf{S}_{t+1}\right)}{\mu_t}(1 - F_{t+1}), \tag{B.14}$$

and $\tilde{\lambda}_t = \frac{\lambda_t}{\mu_t}$ is the scaled Lagrange multiplier on the leverage constraint and $\tilde{\lambda}^d_t = \frac{\lambda^d_t}{\mu_t}$ is the scaled Lagrange multiplier on the deposit constraint.

B.2.3 Aggregate Intermediary Net Worth

At the beginning of each period, a fraction of intermediaries default before paying dividends to shareholders and choosing the portfolio for next period. The government takes ownership of these bankrupt intermediaries and liquidates them to recover some of the outstanding debt. Bankrupt intermediaries are immediately replaced by newly started intermediaries that households endow with initial equity n^0 per intermediary. Then all intermediaries, including newly started ones, solve the identical optimization problem in (B.6).

Denote the aggregate net worth of intermediaries when they solve their decision problem for the next period, by N_t. Then the average net worth of surviving intermediaries in $t+1$ is recursively defined as

$$N^+_{t+1} = \underbrace{\tilde{n}\left(\omega^+_{t+1}, \tilde{a}_{t+1}, \tilde{d}^I_{t+1}, \tilde{b}^I_{t+1}, \mathbf{S}_{t+1}\right)}_{\text{growth rate to t+1}} \underbrace{(1-\phi_0+\tilde{e}_t)\,N_t}_{\text{net worth after payout/issuance in t}},$$

where $\tilde{n}\left(\omega^+_{t+1}, \tilde{a}_{t+1}, \tilde{d}^I_{t+1}, \tilde{b}^I_{t+1}, \mathbf{S}_{t+1}\right)$ is the growth rate of net worth of non-defaulting intermediaries as defined in (B.5). The aggregate net worth of intermediaries thus follows the recursion

$$N_{t+1} = \left(1 - F\left(\omega^*_{t+1}\right)\right) N^+_{t+1} + F\left(\omega^*_{t+1}\right) n^0.$$

Given this expression of intermediary net worth, I can recover all aggregate intermdiary choices, that is, $B^I_{t+1} = \tilde{b}^I_{t+1} N_t$, $D^I_{t+1} = \tilde{d}^I_{t+1} N_t$, $A_{t+1} = \tilde{a}_{t+1} N_t$ and so forth.

B.3 Derivatives of debt price q_t

To obtain the partial derivatives I need to differentiate equation (B.4). Let's first rewrite it as

$$q_t = \mathbb{E}_t\left\{\mathcal{M}_{t,t+1}\left[1 - F_{t+1} + F_{t+1}\left(\pi_{t+1} + (1-\pi_{t+1})\frac{(1-\chi)\mathcal{P}_{t+1}(\omega^-_{t+1})A_{t+1} - D^I_{t+1}}{B^I_{t+1}}\right)\right]\right\}.$$

I can rewrite the recovery value times the probability of default as

$$\mathcal{R}_{t+1} \equiv F_{t+1}\frac{(1-\chi)\mathcal{P}_{t+1}(\omega^-_{t+1})A_{t+1} - D^I_{t+1}}{B^I_{t+1}} = F_{t+1} RV^B_{t+1}, \tag{B.15}$$

where $\omega^-_{t+1} \equiv \mathbb{E}_\omega(\omega_{t+1} \mid \omega_{t+1} < \omega^*_{t+1})$. Recall that ω^*_{t+1} is the default threshold, which satisfies the following equation:

$$\mathcal{P}_{t+1}(\omega^*_{t+1})A_{t+1} - D^I_{t+1} - B^I_{t+1} = 0.$$

First, I compute the derivative of the default threshold with respect to A_{t+1}, D^I_{t+1} and B^I_{t+1} as

$$\begin{aligned}
\frac{\partial \omega^*_{t+1}}{\partial A_{t+1}} &= -\frac{\mathcal{P}_{t+1}(\omega^*_{t+1})}{\mathcal{P}'_{t+1}(\omega^*_{t+1})A_{t+1}} \\
\frac{\partial \omega^*_{t+1}}{\partial D^I_{t+1}} &= \frac{1}{\mathcal{P}'_{t+1}(\omega^*_{t+1})A_{t+1}} \\
\frac{\partial \omega^*_{t+1}}{\partial B^I_{t+1}} &= \frac{1}{\mathcal{P}'_{t+1}(\omega^*_{t+1})A_{t+1}}.
\end{aligned}$$

Then I take derivatives of F_{t+1}:

$$\begin{aligned}
\frac{\partial F_{t+1}}{\partial A_{t+1}} &= f_{\omega,t+1}\frac{\partial \omega^*_{t+1}}{\partial A_{t+1}} \\
\frac{\partial F_{t+1}}{\partial D^I_{t+1}} &= f_{\omega,t+1}\frac{\partial \omega^*_{t+1}}{\partial D^I_{t+1}} \\
\frac{\partial F_{t+1}}{\partial B^I_{t+1}} &= f_{\omega,t+1}\frac{\partial \omega^*_{t+1}}{\partial B^I_{t+1}}.
\end{aligned}$$

Finally, I can differentiate (B.15) to get

$$\begin{aligned}
\frac{\partial \mathcal{R}_{t+1}}{\partial A_{t+1}} &= \left[\frac{F_{t+1}\mathcal{P}_{t+1}(\omega^-_{t+1})}{(B^I_{t+1})} + RV^B_{t+1}\frac{\partial F_{t+1}}{\partial A_{t+1}}\right] \\
\frac{\partial \mathcal{R}_{t+1}}{\partial D^I_{t+1}} &= \left[-\frac{F_{t+1}}{B^I_{t+1}} + RV^B_{t+1}\frac{\partial F_{t+1}}{\partial D^I_{t+1}}\right] \\
\frac{\partial \mathcal{R}_{t+1}}{\partial B^I_{t+1}} &= \left[-\frac{F_{t+1}RV^B_{t+1}}{(B^I_{t+1})} + RV^B_{t+1}\frac{\partial F_{t+1}}{\partial B^I_{t+1}}\right].
\end{aligned}$$

Hence the derivatives of q_t are

$$\begin{aligned}
\frac{\partial q_t}{\partial A^I_{t+1}} &= \mathbb{E}_t\left\{\mathcal{M}_{t,t+1}(1-\pi_{t+1})\left[\frac{\partial \mathcal{R}_{t+1}}{\partial A_{t+1}} - \frac{\partial F_{t+1}}{\partial A_{t+1}}\right]\right\} \\
\frac{\partial q_t}{\partial D^I_{t+1}} &= \mathbb{E}_t\left\{\mathcal{M}_{t,t+1}(1-\pi_{t+1})\left[\frac{\partial \mathcal{R}_{t+1}}{\partial D^I_{t+1}} - \frac{\partial F_{t+1}}{\partial D^I_{t+1}}\right]\right\} \\
\frac{\partial q_t}{\partial B^I_{t+1}} &= \mathbb{E}_t\left\{\mathcal{M}_{t,t+1}(1-\pi_{t+1})\left[\frac{\partial \mathcal{R}_{t+1}}{\partial B^I_{t+1}} - \frac{\partial F_{t+1}}{\partial B^I_{t+1}}\right]\right\}.
\end{aligned}$$

The last piece is the derivative of the loan payoff with respect to ω_t. Define

$$\bar{z}(\omega_t) = \frac{c+1-\delta}{\omega_t},$$

so that

$$\mathcal{P}_t(\omega_t) \;=\; \big[c+1-\delta+\delta p_t\big]\big[1-G(\bar{z})\big] \;+\; \int_{-\infty}^{\bar{z}} z\, dG(z).$$

Then,

$$\begin{aligned}\frac{\partial \mathcal{P}_t}{\partial \omega_t} &= -\big[c+1-\delta+\delta p_t\big]\, g(\bar{z})\, \frac{d\bar{z}}{d\omega_t} \;+\; \bar{z}\, g(\bar{z})\, \frac{d\bar{z}}{d\omega_t} \\ &= \big[\bar{z}-(c+1-\delta+\delta p_t)\big]\, g(\bar{z})\, \frac{d\bar{z}}{d\omega_t},\end{aligned}$$

with $\frac{d\bar{z}}{d\omega_t} = -\frac{c+1-\delta}{\omega_t^2}$. Substituting and replacing $\bar{z} = c+1-\delta/\omega_t$:

$$\frac{\partial \mathcal{P}_t}{\partial \omega_t} = \left[c+1-\delta+\delta p_t - \tfrac{c+1-\delta}{\omega_t}\right] \frac{c+1-\delta}{\omega_t^2}\, g\!\left(\frac{c+1-\delta}{\omega_t}\right).$$

C Model calibration

D Computational solution method

This appendix describes the numerical algorithm that solves the dynamic general equilibrium model laid out in Appendix B. The implementation follows the policy iteration framework of Elenev et al. (2021). I first approximate the unknown policy and transition functions by discretizing the state space and employing multivariate linear interpolation. Starting with an initial guess for the policy and transition functions, I iteratively solve the model at each discretized state-space node. At each node, I compute optimal policies by solving the system of nonlinear equilibrium conditions, reformulating Kuhn–Tucker inequalities as equality constraints suitable for standard nonlinear solvers. Given these solutions, I update the transition functions and repeat the procedure until convergence. This iterative process is fully parallelized across state-space points within each iteration. Finally, I simulate the model forward for many periods using the approximated policy and transition functions. I verify that the simulated trajectories remain within the predefined bounds of the discretized state space. To assess computational accuracy, I calculate relative Euler equation errors along the simulated paths. If trajectories breach the grid boundaries or the approximation errors exceed acceptable thresholds, I refine the grid by adjusting bounds or redistributing points, and repeat the solution procedure.

The state space consists of four exogenous state variables $[Z_t, D_t, d_t, \pi_t]$, and two endogenous state variables $\big[B_t^I, D_t^I\big]$. I first discretize Z_t into a N^Z-state Markov chain using the Rouwenhurst (1995) method. The procedure chooses the productivity grid points

$\{Z_j\}_{j=1}^{N^Z}$ and the $N^Z \times N^Z$ Markov transition matrix $\mathbb{P}_Z$. The same method is used to discretize D_t and π_t. The disaster shock d_t can take on two realizations $\{0, 1\}$. The 2×2 Markov transition matrix between these states is given by $\mathbb{P}_d$. Denote the set of the $N^x = 2 \times N^Z \times N^\pi \times N^D$ values the exogenous state variables can take on as $\mathcal{S}_x = \{Z_j\}_{j=1}^{N^Z} \times \{0, 1\} \times \{\pi_j\}_{j=1}^{N^\pi} \times \{D_j\}_{j=1}^{N^D}$, and the associated Markov transition matrix $\mathbb{P}_x = \mathbb{P}_Z \otimes \mathbb{P}_d \otimes \mathbb{P}_\pi \otimes \mathbb{P}_D$.

The solution algorithm requires the approximation of continuous functions defined on the endogenous state variables. Let the true endogenous state space of the model be defined as follows: each endogenous state variable $S_t \in \{B_t^I, D_t^I\}$ lies within a continuous and convex subset of real numbers characterized by constant state boundaries $[\bar{S}_l, \bar{S}_u]$. Thus, the endogenous state space is given by:

$$\mathcal{S}_n = \left[\bar{B}_l^I, \bar{B}_u^I\right] \times \left[\bar{D}_l^I, \bar{D}_u^I\right].$$

The total state space is then defined as $\mathcal{S} = \mathcal{S}_x \times \mathcal{S}_n$.

To approximate a general function $f : \mathcal{S} \rightarrow \mathbb{R}$, I construct a univariate grid of strictly increasing points (not necessarily equidistant) for each endogenous state variable: $\{B_j^I\}_{j=1}^{N_B}$, $\{D_k^I\}_{k=1}^{N_D}$. These grid points are selected to adequately cover the ergodic distribution of the economy in each dimension, thereby minimizing computational errors. I denote the discretized set of endogenous-state grid points by:

$$\hat{\mathcal{S}}_n = \{B_j^I\}_{j=1}^{N_B} \times \{D_k^I\}_{k=1}^{N_D},$$

and the total discretized state space as $\hat{\mathcal{S}} = \mathcal{S}_x \times \hat{\mathcal{S}}_n$. This discretized state space contains a total of $N^S = N^x \cdot N^B \cdot N^D$ points, each represented as a 2×1 vector corresponding to the two distinct state variables. Given values $\{f_j\}_{j=1}^{N^S}$ of function f at each grid point $\hat{s}_j \in \hat{\mathcal{S}}$, I can approximate f via multivariate linear interpolation. The solution method approximates three distinct sets of functions defined on the domain of state variables:

- **Policy Functions ($\mathcal{C}_P$):** These functions, $\mathcal{C}_P : \mathcal{S} \rightarrow \mathcal{P} \subseteq \mathbb{R}^{N^C}$, determine equilibrium prices, agents' choice variables, and Lagrange multipliers on portfolio constraints. Specifically, the 8 policy functions include bond and deposit prices $q^u(\mathcal{S})$, asset prices $p(\mathcal{S})$, consumption $C(\mathcal{S})$, equity issuance for intermediaries $e(\mathcal{S})$, choices of bonds and deposits for intermediaries $B^I(\mathcal{S}), D^I(\mathcal{S})$, and multipliers on constraints $\lambda^I(\mathcal{S}), \lambda^D(\mathcal{S})$.

- **Transition Functions ($\mathcal{C}_T$):** These functions, $\mathcal{C}_T : \mathcal{S} \times \mathcal{S}_x \rightarrow \mathcal{S}_n$, specify the next-period endogenous state variables as functions of the current state and next-period exogenous shocks. Each endogenous state variable corresponds to one transition function.

- **Forecasting Functions ($\mathcal{C}_F$):** These functions, $\mathcal{C}_F : \mathcal{S} \to \mathcal{F} \subseteq \mathbb{R}^{N^F}$, are used to compute expectations terms required by the equilibrium conditions. Forecasting functions partially overlap with policy functions but include additional terms. In this model, they consist of bond price $q(\mathcal{S})$, consumption $C(\mathcal{S})$, equity issuance $e^I(\mathcal{S})$, household value functions $V(\mathcal{S})$, intermediary value function $V^I(\mathcal{S})$, and the asset price $p(\mathcal{S})$.

Given an initial guess $\mathcal{C}^0 = \{\mathcal{C}_P^0, \mathcal{C}_T^0, \mathcal{C}_F^0\}$, the equilibrium computation algorithm proceeds through the following steps:

Step A: Initialization. Set the current iterate $\mathcal{C}^m = \{\mathcal{C}_P^m, \mathcal{C}_T^m, \mathcal{C}_F^m\} = \{\mathcal{C}_P^0, \mathcal{C}_T^0, \mathcal{C}_F^0\}$.

Step B: Forecasting Values Computation. For each discretized state-space point $s_j \in \hat{\mathcal{S}}$, $j = 1, \ldots, N^S$, perform the following sub-steps:

i. Evaluate the transition functions at s_j combined with each possible realization of the exogenous shocks $x_i \in \mathcal{S}_x$, obtaining next-period endogenous state realizations $s_j'(x_i) = \mathcal{C}_T^m(s_j, x_i)$, for $i = 1, \ldots, N^x$.

ii. Evaluate forecasting functions at these future state realizations, obtaining $f_{i,j}^m = \mathcal{C}_F^m(s_j'(x_i), x_i)$.

This produces an $N^x \times N^S$ forecasting matrix $\mathcal{F}^m$, where each entry is a vector given by:

$$f_{i,j}^m = \left[q_{i,j}, C_{i,j}, e_{i,j}, V_{i,j}, V_{i,j}^I, p_{i,j}\right].$$

Step C: Solving the System of Nonlinear Equations. At each discretized state-space point $s_j \in \hat{\mathcal{S}}$, $j = 1, \ldots, N^S$, solve the nonlinear equilibrium conditions for the corresponding set of 8 policy variables. Given the forecasting matrix $\mathcal{F}^m$ from Step B, solve:

$$\hat{P}_j = \left[\hat{q}_j, \hat{p}_j, \hat{C}_j, \hat{e}_j^I, \hat{B}_j^I, \hat{D}_j^I, \hat{\lambda}_j^I, \hat{\lambda}_j^D\right],$$

where each vector $\hat{P}_j$ satisfies the corresponding equilibrium conditions at s_j. The eight equations are:

$$\hat{q}_j = \mathbb{E}_{s'_{i,j}|s_j}\Big[\hat{\mathcal{M}}_{i,j}\Big\{1-\hat{F}_{i,j}+\hat{F}_{i,j}\Big(\pi_{i,j}+(1-\pi_{i,j})\frac{(1-\chi)\hat{\mathcal{P}}_{i,j}(\omega^-_{i,j})\hat{A}_j-\hat{D}^I_j}{\hat{B}^I_j}\Big)\Big\}\Big], \tag{D.1}$$

$$\hat{p}_j = \frac{\partial\hat{q}_j}{\partial A^I_j}B^I_j+\hat{\lambda}_j\,\xi\hat{p}_j+\mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}\,\hat{\mathcal{P}}_{i,j}(\omega^+_{i,j})\big], \tag{D.2}$$

$$\hat{q}^D_j = \kappa-\frac{\partial\hat{q}_j}{\partial D^I_j}B^I_j+\hat{\lambda}_j+\hat{\lambda}^D_j+\mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}\big], \tag{D.3}$$

$$\hat{q}_j = -\frac{\partial\hat{q}_j}{\partial B^I_j}B^I_j+\hat{\lambda}_j\mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}\big], \tag{D.4}$$

$$\hat{W}_j-\hat{T}_j \geqslant \hat{C}_j+\hat{q}_j\,\hat{B}^I_j+\hat{q}^D_j\,\hat{D}^I_j, \tag{D.5}$$

$$(1-\phi_0)\hat{N}_j+\hat{e}_j = \hat{p}_j\,\hat{A}_j-\hat{q}_j\,\hat{B}^I_j-(\hat{q}^D_j-\kappa)\,\hat{D}^I_j, \tag{D.6}$$

$$\big(\xi\hat{p}_j\hat{A}_j-\hat{B}^I_j-\hat{D}^I_j\big)\,\hat{\lambda}^I_j = 0, \tag{D.7}$$

$$\big(\hat{D}^I_j-\hat{D}^I_j\big)\,\hat{\lambda}^D_j = 0. \tag{D.8}$$

All expectations are weighted sums over the exogenous-state transitions. Variables carrying a hat ($\hat{}$) are *direct functions* of the policy vector $\hat{P}_j$—they are the choice variables passed to the nonlinear solver at state s_j. In contrast, quantities with subscripts $\{i,j\}$ are pre-computed numbers: they depend only on the forecasting vector $\mathcal{F}^m$ from Step B and therefore remain fixed while solving the local system. For example, the stochastic discount factors for households is

$$\hat{\mathcal{M}}_{i,j} \;=\; \beta\left(\tfrac{V_{i,j}}{CE_j}\right)^{\frac{1}{\nu}-\sigma}\left(\tfrac{C_{i,j}}{\hat{C}_j}\right)^{-\frac{1}{\nu}},$$

where $V_{i,j}$ and $C_{i,j}$ come from $\mathcal{F}^m$, while $\hat{C}_j$ is part of the current policy vector being solved for. sumption. To compute the expectation at point s_j, I first look up the corresponding column j in the matrix containing the forecasting values that I computed in step B, $\mathcal{F}^m$. This column contains the N^x vectors, one for each possible realization of the exogenous state, of the forecasting values defined in (F). From these vectors, I need consumption $C_{i,j}$ and the value function $V_{i,j}$. Further, I need current consumption $\hat{C}_j$, which is a policy variable chosen by the nonlinear equation solver. Denoting the probability of moving from current exogenous state x_j to state x_i as $\pi_{i,j}$, I compute the certainty equivalent

$$CE_j = \left[\sum_{x_i|x_j} \pi_{i,j} \left(V_{i,j}\right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}},$$

and then complete expectation as

$$E_{s'_{i,j}|s_j} \left[\hat{\mathcal{M}}_{i,j}\right] = \sum_{x_i|x_j} \pi_{i,j} \beta \left(\frac{V_{i,j}}{CE_j}\right)^{1/\nu-\sigma} \left(\frac{C_{i,j}}{\hat{C}_j}\right)^{-1/\nu}.$$

The mapping of solution and forecasting vectors (P) and (F) into the other expressions in the system follows the same principles and is based on the definitions in Model Appendix B. To solve the system in practice, I use a nonlinear equation solver that relies on a variant of Newton's method, using policy functions $\mathcal{C}_P^m$ as initial guess. The final output of this step is an $N^S \times 8$ matrix $\mathcal{P}^{m+1}$, where each row is the solution vector $\hat{P}_j$ that solves the system above at point s_j.

Step D: Updating Forecasting, Policy, and Transition Functions. Given the new policy matrix $\mathcal{P}^{m+1}$ from Step C, set the policy functions to $\mathcal{C}_P^{m+1} \leftarrow \mathcal{P}^{m+1}$. All forecasting functions except the value functions coincide with the policy functions and are updated in the same way. Hats denote current-policy variables, while subscripts (i, j) refer to fixed forecasting quantities from $\mathcal{F}^m$. For value functions, update

$$\hat{V}_j = \left\{(1-\beta)[\hat{C}_j]^{1-1/\nu} + \beta\, \mathbb{E}_{x_i|x_j}\left[(V_{i,j})^{1-\sigma}\right]^{\frac{1-1/\nu}{1-\sigma}}\right\}^{1/(1-1/\nu)},$$

$$\hat{V}_j^I = \phi_0 N_j^I - \hat{e}_j - \frac{\phi_1}{2}\left(\hat{e}_j\right)^2 + \mathbb{E}_{x_i|x_j}\left[\hat{\mathcal{M}}_{i,j}(1-F_{\omega,i,j})V_{i,j}^I\right].$$

These updated objects form $\hat{\mathcal{C}}_F^{m+1}$. For transition functions, plug the new policies into each law of motion to obtain $\mathcal{C}_T^{m+1}$.

Step E: Convergence Check. Compute

$$\Delta_F = \left\|\mathcal{C}_F^{m+1} - \mathcal{C}_F^m\right\|, \qquad \Delta_T = \left\|\mathcal{C}_T^{m+1} - \mathcal{C}_T^m\right\|.$$

If $\Delta_F < \text{Tol}_F$ *and* $\Delta_T < \text{Tol}_T$, stop and set $\mathcal{C}^* = \mathcal{C}^{m+1}$. Otherwise apply dampening,

$$\mathcal{C}^{m+1} = D\,\mathcal{C}^m + (1-D)\,\hat{\mathcal{C}}^{m+1}, \qquad 0 < D < 1,$$

reset $\mathcal{P}^m \leftarrow \mathcal{P}^{m+1}$, and return to Step B.

Step F: Simulation. With the converged solution $\mathcal{C}^* = \mathcal{C}^{m+1}$ in hand, I simulate the model for $\bar{T} = T_{\text{ini}} + T$ periods.

1. *Exogenous shocks.* The exogenous state x_t follows a Markov chain with transition matrix Π_x. Starting from x_0 and a fixed random seed, I draw $\bar{T} - 1$ uniform random numbers to generate the path $\{x_t\}_{t=1}^{\bar{T}}$ via standard inversion.

2. *Endogenous states.* Given the initial vector $s_0 = [B_0^I, D_0^I, Z_0, D_0, d_0, \pi_0]$, I update $[B_{t+1}^I, D_{t+1}^I] = \mathcal{C}_T^*(s_t, x_{t+1})$, producing the complete sequence $\{s_t\}_{t=1}^{\bar{T}}$.

3. *Burn-in.* I discard the first T_{ini} observations and keep $t = 1, \ldots, T$ to eliminate dependence on initial conditions.

4. *Policy and forecast evaluation.* Along the retained sample I evaluate the policy and forecasting functions, yielding the simulated data set $\{s_t, P_t, f_t\}_{t=1}^{T}$.

D.1 Numerical integration of island shocks

For a given idiosyncratic ("island") shock $\omega_t > 0$, the gross period-t return on the intermediary's loan portfolio is

$$\mathcal{P}_t(\omega_t) = \big[c + (1-\delta) + \delta p_t\big] \int_{\underline{z}(\omega_t, Z_t, d_t)}^{\infty} g(z)\, dz + (1-\eta)\, \omega_t\, Z_t\, e^{-\zeta d_t} \int_0^{\underline{z}(\omega_t, Z_t, d_t)} z\, g(z)\, dz, \tag{D.9}$$

where the default boundary solving $y_t^{i,j} = c + (1-\delta)$ is

$$\underline{z}(\omega_t, Z_t, d_t) = \frac{c + (1-\delta)}{\omega_t\, Z_t\, e^{-\zeta d_t}}. \tag{D.10}$$

Let $\{(x_k, w_k)\}_{k=1}^{K}$ be the K Gauss–Legendre nodes and weights on $[-1, 1]$; transforming them by $z_k = \frac{\bar{z}}{2}(x_k + 1)$ for any upper limit $\bar{z} > 0$ gives

$$\int_0^{\bar{z}} g(z)\, dz \approx \frac{\bar{z}}{2} \sum_{k=1}^{K} w_k\, g(z_k), \qquad \int_0^{\bar{z}} z\, g(z)\, dz \approx \frac{\bar{z}}{2} \sum_{k=1}^{K} w_k\, z_k\, g(z_k). \tag{D.11}$$

Because $\int_{\underline{z}}^{\infty} g(z)\,dz = 1 - \int_0^{\underline{z}} g(z)\,dz$, substituting $\bar{z} = \underline{z}(\omega_t, Z_t, d_t)$ from (14) into (D.11) delivers the quadrature approximation

$$\widehat{\mathcal{P}}_t(\omega_t) = \big[c + (1-\delta) + \delta p_t\big]\Bigg[1 - \frac{\underline{z}}{2}\sum_{k=1}^{K} w_k\, g(z_k)\Bigg] + (1-\eta)\,\omega_t\, Z_t\, e^{-\zeta d_t}\frac{\underline{z}}{2}\sum_{k=1}^{K} w_k\, z_k\, g(z_k), \tag{D.12}$$

where $z_k = \frac{\underline{z}}{2}(x_k + 1)$. The same Gauss–Legendre grid also discretises the shock itself: for $\omega \sim \mathrm{Log}\mathcal{N}(1, \sigma_\omega^2)$ with $\log\omega \sim \mathcal{N}(\hat{\mu}, \hat{\sigma}^2)$, where $\hat{\sigma}^2 = \log(1 + \sigma_\omega^2)$ and $\hat{\mu} = -\frac{1}{2}\hat{\sigma}^2$, each node gives $\omega_k = \exp\big(\hat{\mu} + \hat{\sigma}\,\Phi^{-1}(\frac{x_k+1}{2})\big)$ and any smooth $F(\omega)$ satisfies $\mathbb{E}[F(\omega)] \approx \frac{1}{2}\sum_{k=1}^{K} w_k\, F(\omega_k)$. Choosing $K = 7$ yields machine-precision accuracy with negligible computational cost.

D.2 Evaluating the solution

To evaluate solution quality I perform two checks along the simulated sample path.

1. *Grid extendash boundary check.* I verify that each simulated state remains inside the grids defined in Step A. Whenever a trajectory exits a bound I enlarge the affected grid range and restart the algorithm from Step A. I also create histogram plots for the endogenous state variables, overlaid with the placement of grid points. These types of plots allow us to check the quality of the grid approximation and that the simulated path of the economy does not violate the state grid boundaries. It further helps us to determine where to place grid points. Histogram plots for the benchmark economy are in Figure XXXX.

2. *Relative Euler extendash error check.* For every period t and every equilibrium condition and transition law of motion ℓ, I compute the relative error

$$\varepsilon_t^{(\ell)} = 1 - \frac{\mathrm{RHS}_t^{(\ell)}}{\mathrm{LHS}_t^{(\ell)}},$$

scaling by a representative endogenous variable taken from the equation. I report the average, median, and tail percentiles of $|\varepsilon_t^{(\ell)}|$. Excessive errors trigger a local grid refinement and a fresh solve–simulate cycle. Table XXXX reports the median error, the 95th percentile of the error distribution, the 99th, and the 100th percentiles during the simulation of the model. Median and 75th percentile errors are small for all equations. Maximum errors are on the order of X% for equations XXXX. It is possible to reduce these errors by placing more grid points in those areas of the state space but adding points to eliminate the tail errors has little to no effect on any of the results at the cost of increased computation times.

E Details of counterfactuals experiments

I now detail the counterfactual experiment of Section 7. First, I explain how I use the particle filter to extract information on the sequence of $\{\pi_t\}$. Second, I discuss how I generate the decomposition of Figure 9. For annual data 2004–2015, the nonlinear state–space system is

$$\begin{aligned}\mathbf{Y}_t &= \mathbf{g}(\mathbf{S}_t) + \boldsymbol{\eta}_t,\\ \mathbf{S}_t &= \mathbf{f}(\mathbf{S}_{t-1}, \boldsymbol{\varepsilon}_t),\end{aligned} \tag{E.1}$$

where the 4×1 state vector and structural innovations are

$$\mathbf{S}_t = \left[D_t,\ \pi_t,\ Z_t,\ d_t\right]^\top, \qquad \boldsymbol{\varepsilon}_t = \left[\varepsilon_t^B,\ \varepsilon_t^\pi,\ \varepsilon_t^Z,\ \varepsilon_t^d\right]^\top.$$

The 3×1 measurement vector contains the one–year credit-spread differential, the risk-neutral default probability constructed in Section 3 and the deposit bound:

$$\mathbf{Y}_t = \left[CS_{t,365},\ Q^*_{t,365},\ \Delta D_t\right]^\top, \quad CS_{t,365} \equiv r_{t,365} - r^{rf}_{t,365}.$$

To respect the positive support and skewness of observed spreads I set

$$CS^{data}_{t,365} = g_1(\mathbf{S}_t)\ \exp(\eta_t^{CS}), \qquad \eta_t^{CS} \sim \mathcal{N}\!\left(-\tfrac{1}{2}\sigma^2_{CS},\ \sigma^2_{CS}\right),$$

while the empirical default probability obeys a shifted beta law,

$$Q^{*\,data}_{t,365} = g_2(\mathbf{S}_t) + \eta_t^Q, \qquad \eta_t^Q \sim \text{Beta}\!\left(\alpha_t, \beta_t\right) - \mathbb{E}[\text{Beta}(\alpha_t, \beta_t)].$$

Each quarter the beta parameters

$$\alpha_t = \left[(1-\mu_t)/\nu_t - \mu_t\right]\mu_t^2, \quad \beta_t = \alpha_t\left(1/\mu_t - 1\right)$$

match the filtered mean $\mu_t = g_2(\mathbf{S}_t)$ and variance $\nu_t = 0.01\,\hat{\sigma}^2(Q^{*\,data}_{t,365})$, while $\sigma^2_{CS} = 0.01\,\hat{\sigma}^2(CS^{data}_{t,365})$. Only $CS_{t,365}$ and $Q^*_{t,365}$ carry measurement noise; the innovation ΔD_t is observed without error.

Let $\mathbf{Y}^t = [\mathbf{Y}_1, \ldots, \mathbf{Y}_t]$ denote the history of observed vectors up to time t, and write

$$p(\mathbf{S}_t \mid \mathbf{Y}^t)$$

for the conditional law of the (latent) state vector. No closed-form expression exists for $p(\mathbf{S}_t \mid \mathbf{Y}^t)$ and therefore I approximate it at every t with an auxiliary particle filter that maintains a collection of weighted particles $\{(\mathbf{S}_t^i, \tilde{w}_t^i)\}_{i=1}^N$ such that, for any integrable function f,

$$\frac{1}{N}\sum_{i=1}^{N} f(\mathbf{S}_t^i)\,\tilde{w}_t^i \xrightarrow{\text{a.s.}} \mathbb{E}\big[f(\mathbf{S}_t) \mid \mathbf{Y}^t\big].$$

The mean of the simulated particles then provides a smoothed path for the unobserved state.

Each recursion proceeds as follows:

1. **Initialisation ($t = 0$).** Draw an initial cloud $\{\mathbf{S}_0^i\}_{i=1}^N$ from a suitable prior and set the associated (unnormalised) weights to $\tilde{w}_0^i = 1$ for all i.

2. **Prediction (time t).** For each particle $i = 1, \dots, N$, simulate a forecast state

$$\mathbf{S}_{t|t-1}^i \sim p(\mathbf{S}_t \mid \mathbf{S}_{t-1}^i)$$

   using the state-transition simulator described in Online Appendix D.

3. **Updating of importance weights.** Compute the incremental weight for every forecast particle as

$$w_t^i = p\big(\mathbf{Y}_t \mid \mathbf{S}_{t|t-1}^i\big)\,\tilde{w}_{t-1}^i.$$

4. **Normalisation and resampling.**
   (a) Normalise the unnormalised weights so they sum to one: $\tilde{w}_t^i = w_t^i \Big/ \sum_{j=1}^N w_t^j$.
   (b) Draw $N = 100000$ particles *with replacement* from $\{\mathbf{S}_{t|t-1}^i, \tilde{w}_t^i\}_{i=1}^N$ and re-label the resampled set as $\{\mathbf{S}_t^i\}_{i=1}^N$.
   (c) Reset all weights to unity, $\tilde{w}_t^i = 1$.

5. **Iterate.** If $t < T$, increase $t \leftarrow t + 1$ and return to Step 2; otherwise terminate.

The next step is to decompose the counterfactual into its components. I now discuss how I use the approximation to $\{p\left(\mathbf{S}_t \mid \mathbf{Y}^t\right)\}_{t=2004}^{2015}$ along with the structural model to generate the decomposition presented in Figure 9.

Define the model-implied credit spread

$$\widehat{CS}_{t,365} = \sum_{i=1}^{N} g_1(\mathbf{S}_t^{(i)})\,\tilde{w}_t^{(i)},$$

where $g_1(\mathbf{S}_t)$ is the policy function for the credit spread differential. The measurement error is

$$\eta_t^{CS} = CS_{t,365}^{\text{data}} - \widehat{CS}_{t,365}.$$

I generate the fundamenta component by freezing the bailout probability at its pre-crisis level and backing up the spread

$$\widehat{CS}^{\text{fund}}_{t,365} = \sum_{i=1}^{N} g_1\Big(\mathbf{S}_t^{(i)} \mid \pi_{t+1} = \bar{\pi}^H\Big)\, \tilde{w}_t^{(i)},$$

The bailout component is then

$$\Delta_t^{\text{Bailout}} = \widehat{CS}_{t,365} - \widehat{CS}^{\text{fund}}_{t,365}.$$

The same procedure is applied for the counterfafctual with fixed $B_{t+1} = \bar{B}$ where $\bar{B}$ is the ergodic mean of the leverage.

F Model extensions

F.1 Equity injections

F.2 Bank assets

In this section I consider an extension of the model in which intermediaries do not hold the entire pool of risky assets. To be the case, I assume that now also households can invest in debt claims as intermediaries A^H_{t+1}. However, households do not have access to the intermediaries' superior (costless) monitoring technology. They can hold corporate debt that does not require screening and monitoring, such as highly rated corporate bonds, without incurring any monitoring cost. A subset of the total supply of corporate debt $\varphi_0 < 1$ satisfies this requirement. If households want to expand (or shrink) their holdings of corporate debt away from the amount φ_0, they incur costs: $\Phi^H(A^H_{t+1}) = \frac{\varphi_1}{2}\left(\frac{A^H_{t+1}}{\varphi_0} - 1\right)^2 \varphi_0$ (Brunnermeier & Sannikov 2014, Elenev et al. 2021). In equilibrium, it must be the case that $A^H_t = 1 - A_t$ and that the resource constraint is satisfied such that

$$\begin{aligned} Z_t e^{-d_t\zeta} = C_t + \Phi^e\left(e_t/N_t\right) + \chi A_t \int_{\omega\in\mathcal{D}_t} \mathcal{P}_t(\omega) f(\omega) d\omega \\ + \eta Z_t e^{-\zeta d_t} \int\int_0^{\underline{z}(\omega_t, Z_t, d_t)} \omega z\, g(z) f(\omega)\, dz\, d\omega + \Phi^H(A^H_{t+1}). \end{aligned} \tag{F.1}$$

One interpretation is that the household represents other intermediairies who are participants in the same asset markets of the banks (e.g. shadow banks/non-bank financial intermediaries). Another potential intepretation is that they represent a costly securitization techonolgy which allows banks to sell aggregate risk off their balance sheet. The household first order condition then reads

$$p_t = \mathbb{E}_t\left\{\mathcal{M}_{t,t+1}\int \mathcal{P}_{t+1}(\omega)f(\omega)d\omega\right\} + \Phi^{H,\prime}(A^H_{t+1}). \tag{F.2}$$

Importantly, the household holds a diversified portfolio of debt claims differently from the intermediaries.

G Simple economy

G.1 Environment

Agents, preferences and endowments. There are two periods, $t = 1, 2$ and a single consumption good (dollar), which serves as numeraire. The economy is populated by a unit measure of risk-neutral consumers indexed by C, and intermediaries indexed by I, and a government. There is also a social planner/regulator/government, who sets bailouts and leverage regulation. I denote the possible states of nature at date 1 by $\omega \in [0, \bar{\omega}]$. As described below, ω corresponds to the realization of the returns to intermediaries' technology. Consumers discount the future with a discount factor β and own debt and equity of intermediaries. The endowments of the consumption goods of consumers at date 1 and 2 are $\{n^C_1, n^C_2(\omega)\}$. The budget constraint of intermediaries at date 0 is given by

$$d_1 = q(b, a)b - pa,$$

where p denotes the price of asset, $q(b, a)$ the price of debt, b the face value of debt, a the amount of asset purchased, and d_1 is the equity issued if $d_1 < 0$ or the dividend paid if $d_1 > 0$. The budget constraint of intermediaries at date 1 in state ω is given by

$$d_2(\omega) = \max\{\omega a - b, 0\}.$$

The budget constraint of consumers at date 1 and at date 2 in state ω are given by

$$\begin{aligned} c_1 &= n^C_1 - q(b, k)b + d_1, \\ c_2(\omega) &= n^C_2(\omega) + d_2(\omega) + b\left(\mathbb{I}_{\{\omega a \geqslant b\}} + \pi\mathbb{I}_{\{\omega a < b\}} + (1-\pi)\chi\frac{\omega a}{b}\mathbb{I}_{\{\omega a < b\}}\right) - T_2. \end{aligned}$$

The budget constraint in period 1 equalizes the consumption of consumers and with the savings in debt $q(b, a)b$ and equity to intermediaries. The budget constraint in period 2 equalizes the consumption of consumers with the face value of debt b for every realization of the state ω and intermediaries dividends net of transfers from government T_2.

Technology and financial contracts. At time 1, intermediaries choose how much asset, a, at price p to buy. By time 2, the intermediaries' assets generate a random return $\omega \geqslant 0$, which follows a distribution $F(\omega) \equiv F$ with $supp(\omega) = [0, \bar{\omega})$. For simplicity, I assume that $\int \omega dF(\omega) = 1$. Intermediaries finance their investment by issuing debt with face value b, and price $q(b, k)$. I define leverage as the ratio of debt over assets, $\ell = \frac{b}{a}$. It needs to raise the difference in equity. Post-realization of returns in period 2, intermediaries choose whether to default or not. If the intermediaries default, shareholders receive nothing while financiers are bailed out with probability π by the government, in which case they receive b per unit of capital, otherwise, they receive $\chi\omega$ per unit of investment, where $0 \leqslant \chi \leqslant 1$. The remainder $(1-\chi)\omega$ measures the deadweight loss or costs associated with default. If the intermediaries do not default, financiers are paid b and shareholders receive the residual claim $(1-\phi)(\omega a - b)$ in the form of dividends. ϕ captures the costs of equity issuance or tax advantage of debt. Costs of default and equity issuance costs ensures a non-trivial choice of capital structure. I assume that the costs of bank equity are private and so that $\phi(\omega a - b)$ is reimbursed to the consumers in the form of lump sum transfers. Making the costs of equity social would not impact the results qualitatively.

Regulation. The government finances bailouts by raising lump sum taxes from consumers in period 2. The government balances his budget period by period so that

$$T_2 = \int_0^{\ell} \pi \left(\ell - \chi\omega\right) dF(\omega).$$

The government is also able to impose a leverage cap on intermediaries at date 1. Formally, the governme requires that intermediaries set $\ell \leqslant \xi$, where $1-\xi$ is the minimal permitted ratio of equity contribution to risky investment. This constraint imposes a leverage cap, or equivalently, a minimal equity contribution per unit of investment.

Equilibrium definition. An equilibrium is defined as a set of intermediary's capital structure $d_1, b, a, d_2(\omega)$ and default decision, prices for intermediaries debt q and assets p, such that (i) intermediaries maximize their expected net present value while taking into account that any debt issued is valued by consumers, (ii) consumers maximize their utility and (iii) the capital market clears, $a = 1$.

My notion of equilibrium, in which intermediaries internalize that their borrowing decisions affect their cost of financing in equilibrium, is standard in models of default.

G.2 Equilibrium characterization

I introduce Lemma 1 which presents a reformulation of the intermediary problem whose solution characterize equilibrium leverage.

Lemma 1 (Intermediaries' problem)**.** *Equilibrium leverage is given by the solution to the following reformulation of the problem faced by intermediaries:*

$$\nu = \max_{\ell} q(\ell)\ell - p + \beta^{I} \int_{\ell}^{\bar{\omega}} (\omega - \ell) dF(\omega) \tag{G.1}$$

where $\beta(1-\phi) = \beta^{I}$*, subject to the leverage constraint and the debt pricing equation*

$$\ell \leqslant \xi, \tag{G.2}$$

$$q(\ell) = \beta \left[\int_{\ell}^{\bar{\omega}} dF(\omega) + \int_{0}^{\ell} \left(\pi + (1-\pi)\frac{\chi\omega}{\ell} \right) dF(\omega) \right]. \tag{G.3}$$

The size decision of the intermediary is then given by

$$\max_{a \geqslant 0} a\nu.$$

Proof of Lemma 1. The problem that intermediary face at date 1, after anticipating their optimal default decision, can be expressed as follows:

$$V = \max_{b,a,d_1,d_2(\omega)} d_1 + \beta(1-\phi) \int d_2(\omega) dF(\omega)$$

subject to budget constraints at date 1 and in each possible state $\{\omega, \pi\}$ at date 1, the capital requirement and the consumers' debt pricing equation

$$d_1 = q(b,a)b - pa, \tag{G.4}$$

$$d_2(\omega) = \max\{\omega a - b, 0\}, \forall \omega \tag{G.5}$$

$$\frac{b}{a} \leqslant \xi, \tag{G.6}$$

$$q(b,a) = \beta \left[\int_{\frac{b}{a}}^{\bar{\omega}} dF(\omega) + \int_{0}^{\frac{b}{a}} \left(\pi + (1-\pi)\frac{\chi\omega a}{b} \right) dF(\omega) \right]. \tag{G.7}$$

Financiers take into account that higher intermediary leverage increases the probability of a default. The intermediary internalizes this effect when making its leverage decision.

First, notice that intermediaries optimally default at date 1 whenever $\omega < \ell$, and repay when $\omega \geqslant \ell$. To solve the intermediary problem, divide the intermediary objective by a

to get

$$v = \max_{\ell} d_1 + \beta(1-\phi)\int_{\ell}^{\bar{\omega}}(\omega-\ell)dF(\omega)$$

subject to the budget constraint at date 0 and the debt pricing equation

$$d_1 = q(\ell)\ell - p \tag{G.8}$$

$$\ell \leqslant \xi, \tag{G.9}$$

$$q(\ell) = \beta\left[\int_{\ell}^{\bar{\omega}} dF(\omega) + \int_0^{\ell}\left(\pi + (1-\pi)\frac{\chi\omega}{\ell}\right) dF(\omega)\right]. \tag{G.10}$$

Substituting period 1 budget constraint into the objective function, I can rewrite the problem as in the statement of the lemma. The size decision of the intermediary is then given by

$$\max_{a \geqslant 0} av.$$

□

It is possible to fully characterize the equilibrium of the model by incorporating the default decision of intermediaries at date 1 and the pricing of debt by consumers into the intermediaries' date 0 problem. First, notice that intermediaries optimally default at date 1 whenever $\omega < \ell$, and repay when $\omega \geqslant \ell$. The first component of the objective function represents the equity issued/dividends paid by the intermediary in period 0 to the consumers . The second component in equation (G.1) corresponds to the present value of the equity payoffs. Since consumers are only paid in the non-default states, this integral is over states in which $\omega \geqslant \ell$. The first constraint is the leverage constraint, which states that the ratio of debt over assets cannot exceed ξ. The second constraint corresponds to the present value of the debt payoffs in default states (per unit), as perceived by consumers. When intermediaries default ($\omega < \ell$), consumers receive $\chi\omega$ per unit of investment, which accounts for the deadweight losses of default. Intermediaries do not directly benefit from government bailouts, and their objective function simply corresponds to their market value at date 2. Nevertheless, markets generate implicit incentives to capture government bailouts, because the implicit subsidy is accounted for in security prices.

I am now ready to characterize the optimal solution to the intermediary problem in the following proposition.

Proposition 1 (Equilibrium leverage). *Equilibrium leverage $\ell^{\star}$ is given by the solution to*

$$\frac{d\nu\left(\ell^{\star}\right)}{d\ell} = \underbrace{\beta\int_{0}^{\ell}\pi dF(\omega) + \left(\beta - \beta^{I}\right)\int_{\ell}^{\bar{\omega}} dF(\omega)}_{\substack{\textit{marginal benefits} \\ \textit{(subsidy + valuation difference)}}} - \underbrace{\beta(1-\pi)(1-\chi)\ell f(\ell)}_{\substack{\textit{marginal costs} \\ \textit{(distress)}}} = \lambda. \tag{G.11}$$

where λ is the Lagrange multiplier associated with the leverage constraint.

Three forces determine the marginal value of leverage, characterized in Equation (G.11). The first force corresponds to the additional leverage an intermediary is able to raise because of the bailout subsidy in present value terms. The second force arises due to the differences in valuation between intermediaries and consumers. By increasing the leverage ratio ℓ, an intermediary is able to raise in present value terms $\beta(1 - F(\ell))$ dollars per unit invested, whose repayment cost in present value terms corresponds to $\beta(1 - \phi)(1 - F(\ell))$. This second force is proportional to the difference in discount factors $\beta - \beta^{I} > 0$. The third force corresponds to the marginal increase in deadweight losses associated with defaulting more frequently after increasing leverage. These three forces guarantee that equilibrium leverage is strictly positive.

Notice that

$$\frac{d\nu\left(\ell\right)}{d\ell}\ |_{\ell=0} = \beta - \beta^{I} > 0,$$

so that the intermediary find it optimal to choose non-negative leverage in equilibrium. Therefore, for a given leverage constraint ξ, my problem always features a solution for leverage in $[0, \xi]$. The presence of bailout subsidies imply that intermediary would lever up to the maximum leverage constraint ξ given the linearity of their problem so that $\ell = \xi$.

Note that a positive amount of bank investment $a > 0$ in equilibrium requires that the expected profit per unit is zero, $\nu = 0$, which when combined with equation (G.1) gives intermediaries willingness to pay for a dollar of risky assets as

$$p = q(\xi)\xi + \beta^{I}\int_{\xi}^{\bar{\omega}}(\omega - \xi)dF(\omega). \tag{G.12}$$

which corresponds the present value of the expected payoffs of the intermediary's assets. The first term corresponds to the present value of the expected payoffs of the debt issued by the intermediary, while the second term corresponds to the present value of the expected payoffs of the equity issued by the intermediary.

G.3 Comparative statics

First, I show how the equilibrium asset price p changes with the bailout probability π and the leverage constraint ξ.

Lemma 2. *The intermediaries willingnes to pay for a dollar of risky assets* p *is increasing in the bailout probability* π *and in the leverage constraint* ξ. *The debt price* q *is increasing in the bailout probability* π *and decreasing in the leverage constraint* ξ.

Proof of Lemma 2. I start with studying changes in ξ. Given the expression for the asset price,

$$\begin{aligned} p &= \beta\left[\int_{\xi}^{\bar{\omega}} \xi dF(\omega) + \int_0^{\xi} (\pi\xi + (1-\pi)\chi\omega)\, dF(\omega)\right] + \beta^I \int_{\xi}^{\bar{\omega}} (\omega - \xi) dF(\omega), \\ &= \beta \int_0^{\xi} (\pi\xi + (1-\pi)\chi\omega)\, dF(\omega) + \int_{\xi}^{\bar{\omega}} (\beta^I\omega + (\beta - \beta^I)\xi) dF(\omega), \end{aligned}$$

I can differentiate the asset price with respect to ξ:

$$\frac{\partial p}{\partial \xi} = q(\xi) + \xi \frac{\partial q}{\partial \xi} - \beta^I(1 - F(\xi)).$$

By using the first order condition for leverage evaluated at $\ell = \xi$, I can express the derivative as exactly the marginal value of leverage, λ, which is positive. Therefore, the asset price is increasing in ξ. Secondly, the asset price is increasing in π since

$$\frac{\partial p}{\partial \pi} = \xi \frac{\partial q}{\partial \pi} = \beta \int_0^{\xi} (\xi - \chi\omega)\, dF(\omega) > 0.$$

Finally, the debt price is increasing in π since

$$\frac{\partial q}{\partial \pi} = \beta \int_0^{\xi} (\xi - \chi\omega)\, dF(\omega) > 0,$$

and decreasing in ξ since

$$\frac{\partial q}{\partial \pi} = -\beta(1-\pi)\left\{ f(\xi)\left[1 - \tfrac{\chi\omega}{\xi}\right] + \tfrac{\chi\omega}{\xi^2} F(\xi) \right\} < 0.$$

□

Second, I am interested in understanding how the sensitivity of asset prices to bailout probabilities and leverage constraints changes with riskiness of the asset. To do so, I wanto to compare the derivatives characterized in Lemma 2 under perturbations of the distribution of the asset returns. Since I have specified flexible distributions of asset returns, I will characterize how the asset price sensitives to bailout probability and leverage change with changes in the risky asset payoff distribution using variational (Gateaux) derivatives. Formally, I consider perturbations of the form

$$F(\omega) + \varepsilon G(\omega),$$

where $F(\omega)$ denotes the original cumulative distribution function of ω, the variation $G(\omega)$ represents the direction of the perturbation, and $\varepsilon \geqslant 0$ is a scalar. When $G(\omega) < 0$, it is natural to say that for the perturbed distribution the probability assigned to states equal or lower than ω is now higher. I consider variations $G(\omega)$ that are continuously differentiable and satisfy $G(0) = G(\bar{\omega}) = 0$. These conditions ensure that perturbed beliefs are still valid cumulative distribution functions for small enough values of ε. In particular, I analyze perturbations $G(\omega)$ that induce lower risk in the sense of hazard-rate dominance. Formally, an absolutely continuous distribution $F(\omega)$ becomes less risky in the sense of hazard-rate dominance if the hazard rate $h(\omega) \equiv \frac{f(\omega)}{1-F(\omega)}$ decreases for all ω. This is a stronger requirement than first-order stochastic dominance, but a weaker requirement than the monotone likelihood ratio property. Therefore, in terms of variational derivatives, a perturbation $G(\omega)$ induces optimism in a hazard-rate sense if $\frac{\delta h(\omega)}{\delta F} \cdot G \leqslant 0$ for all ω (Dávila & Walther 2023).

Lemma 3. *The sensitivity of the asset price* p *to the bailout probability* π *and the leverage constraint* ξ *in response to changes in the distribution of the asset payoffs is given by the following variational derivatives:*

$$\frac{\delta \frac{dp}{d\pi}}{\delta F} \cdot G = \beta G(\xi)\xi(1-\chi) + \beta\chi \int_0^{\xi} G(\omega)d\omega,$$
$$\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G = -G(\xi)\left(-\beta\pi + (\beta - \beta^I) + \beta(1-\pi)(1-\chi)\xi\frac{g(\xi)}{G(\xi)}\right).$$

If I consider hazard-rate dominant perturbations, so that $G(\omega) < 0$ *then the first derivative is negative and the second derivative is ambiguos and inversely related to* π.

Proof of Lemma 3. Before proving the results, I prove the property of hazard rate perturbations that I will use to show the main results of the lemma. The hazard rate after an arbitrary perturbation is given by $h(\omega) = \frac{f(\omega)+\varepsilon g(\omega)}{1-(F(\omega)+\varepsilon G(\omega))}$. Its derivative with respect to ε takes the form

$$\frac{dh(\omega)}{d\varepsilon} = \frac{g(\omega)}{1-(F(\omega)+\varepsilon G(\omega))} + \frac{(f(\omega)+\varepsilon g(\omega))G(\omega)}{(1-(F(\omega)+\varepsilon G(\omega)))^2}.$$

In the limit in which $\varepsilon \to 0$, for hazard-rate dominance to hold, it must be the case that $\lim_{\varepsilon \to 0} \frac{dh(\omega)}{d\varepsilon} < 0$, therefore

$$
\begin{aligned}
\lim_{\varepsilon \to 0} \frac{dh(\omega)}{d\varepsilon} &= \frac{g(\omega)}{1-F(\omega)} + \frac{f(\omega)}{1-F(\omega)} \frac{G(\omega)}{1-F(\omega)} < 0 \\
&\iff g(\omega) + \frac{f(\omega)}{1-F(\omega)} G(\omega) < 0 \\
&\iff \frac{g(\omega)}{G(\omega)} + \frac{f(\omega)}{1-F(\omega)} > 0 \\
&\iff \frac{f(\omega)}{1-F(\omega)} > -\frac{g(\omega)}{G(\omega)}
\end{aligned}
$$

where in the second-to-last line the sign of the inequality flips because $G(\omega)$ is negative, since hazard-rate dominance implies first-order stochastic dominance. I compute $\frac{\delta \frac{dp}{d\pi}}{\delta F} \cdot G$ as follows:

$$
\begin{aligned}
\frac{\delta \frac{dp}{d\pi}}{\delta F} \cdot G &= \lim_{\varepsilon \to 0} \frac{\left(\beta \int_0^{\xi} (\xi - \chi\omega)\, d\left(F + \varepsilon G\right)\right) - \left(\beta \int_0^{\chi} (\xi - \chi\omega)\, dF\right)}{\varepsilon} \\
&= \beta \left(\int_0^{\xi} (\xi - \chi\omega)\, dG(\omega) \right) = \beta G(\xi)\xi - \beta\chi \int_0^{\xi} \omega dG(\omega) \\
&= \beta G(\xi)\xi(1-\chi) + \beta\chi \int_0^{\xi} G(\omega) d\omega,
\end{aligned}
$$

where the last equality follows after integrating by parts. If I consider a distribution G that dominates F is an hazard rate sense, $G(\omega) < 0$, then it is clear that the derivative is negative. In the same way, I can compute $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G$ as follows:

$$
\begin{aligned}
\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G &= \beta\pi G(\xi) + (\beta - \beta^I)(1 - G(\xi)) - \beta(1-\pi)(1-\chi)\xi g(\xi) \\
&= -G(\xi) \left(-\beta\pi + (\beta - \beta^I) + \beta(1-\pi)(1-\chi)\xi \frac{g(\xi)}{G(\xi)} \right).
\end{aligned}
$$

If I consider a distrbution G that dominates F is an hazard rate sense, $G(\omega) < 0$, then it is sufficient to study the sign of the term in the parenthesis :

$$
-\beta\pi + (\beta - \beta^I) + \beta(1-\pi)(1-\chi)\xi \frac{g(\xi)}{G(\xi)}.
$$

At an interior optimum, Equation (G.11) implies that

$$
\frac{dp}{d\xi} = \frac{\beta\pi}{1-F(\xi)} - \beta\pi + \beta - \beta^I - \beta(1-\chi)(1-\pi)\xi \frac{f(\xi)}{1-F(\xi)} = \lambda \geqslant 0
$$

or, equivalently,

$$\beta(1-\pi)-\beta^{I} \geqslant \beta(1-\chi)(1-\pi)\xi\frac{f(\xi)}{1-F(\xi)}-\frac{\beta\pi}{1-F(\xi)}.$$

Hazard-rate dominance implies that $\frac{f(\omega)}{1-F(\omega)} \geqslant -\frac{g(\omega)}{G(\omega)}$, so the following relation holds:

$$\beta(1-\pi)-\beta^{I} \geqslant -\beta(1-\pi)(1-\chi)\xi\frac{g(\xi)}{G(\xi)}+\frac{\beta\pi g(\xi)}{f(\xi)G(\xi)}$$

The sign of the expression is ambiguos and in particular it depends on the extent to which creditors are bailed out. In particular, in the limit as π approaches 0, the term is positive, and so the sign of the derivative is positive. But as π approaches 1, the term can turn into negative as the bailout likelihood decreases the distress costs arising from default. This can make the derivative negative. □

The first derivative is negative under hazard-rate dominance ($G(\omega) \geqslant 0$). A less risky distribution dampens the effect of bailouts (πx) on asset prices. Bailouts become more impactful in riskier environments because higher default risk (more mass at $\omega < \xi$) increases the value of bailout guarantees; greater exposure to low- ω states ($\int_0^{\xi} G(\omega)d\omega \geqslant 0$) raises the implicit subsidy from bailouts. If the payoff distribution is has less mass under the left tail (lower default likelihood), the bailout subsidy becomes less valuable. When F shifts toward safer states ($G(\omega) < 0$), intermediaries and consumers anticipate lower bailout transfers, which deflate asset prices. This makes bailout policies less potent in propping up prices when assets are safer.

On the other hand, the sign of the variational derivative $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G$ depends critically on the bailout probability π. The net effect is determined by the balance of three components:

$$\underbrace{-\beta\pi}_{\substack{\text{Reduced marginal benefit}\\ \text{from bailouts}}} \quad + \quad \underbrace{(\beta-\beta^{I})}_{\substack{\text{Valuation difference}\\ \text{(debt vs. equity)}}} \quad + \underbrace{\beta(1-\pi)(1-\chi)\xi\frac{g(\xi)}{G(\xi)}}_{\substack{\text{Marginal default cost}\\ \text{amplified by risk}}}.$$

When $\pi \approx 0$, the net effect simplifies to:

$$(\beta-\beta^{I})+\beta(1-\chi)\xi\frac{g(\xi)}{G(\xi)} > 0,$$

implying $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G > 0$. A safer distribution ($G(\xi) < 0$) increases the price sensitivity to leverage constraints, as default costs are less important. Conversely, when $\pi \approx 1$, the net effect becomes:

$$-\beta + (\beta - \beta^I) < 0,$$

yielding $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G < 0$. With full bailouts, safer distributions decreases price sensitivity to leverage constraints, as bailouts subsidize default risk. This non-monotonicity reflects the interplay between bailout subsidies, valuation differences, and default costs. Policymakers must account for both asset riskiness and bailout expectations when designing leverage constraints: higher capital requirements depress intermediaries willingness to pay for risky assets, but the effect is more pronounced when more bailouts are expected.

G.4 Variance of equity returns, bailouts and regulation

With a binding leverage cap $\ell = \xi$, per-unit-asset equity pays

$$\tilde{e}(\omega) = \big(1 - \phi\big)\,(\omega - \xi)\,\mathbf{1}_{\{\omega \geqslant \xi\}}, \quad E_0 = \beta^I \underbrace{\int_{\xi}^{\bar{\omega}} (\omega - \xi)\, dF(\omega)}_{= A(\xi)},$$

so the gross equity return per dollar of initial equity is

$$R_E(\omega) = \frac{\tilde{e}(\omega)}{E_0} = \frac{(\omega - \xi)\mathbf{1}_{\{\omega \geqslant \xi\}}}{A(\xi)}, \qquad \mathbb{E}[R_E] = 1.$$

Define[3]

$$\sigma_L^2(\xi) := F(\xi), \qquad \sigma_R^2(\xi) := \int_{\xi}^{\bar{\omega}} \big(R_E(\omega) - 1\big)^2\, dF(\omega),$$

so that total variance satisfies

$$\sigma_E^2(\xi) = \sigma_L^2(\xi) + \sigma_R^2(\xi) \;=\; \frac{B(\xi)}{A(\xi)^2} - 1,$$

because $\sigma_L^2 = F(\xi)$ and $\sigma_R^2 = (B/A^2) - 1 - F(\xi)$. Using $A'(\xi) = -(1 - F(\xi))$, $B'(\xi) = -2A(\xi)$, one obtains

$$\boxed{\frac{\partial \sigma_L^2}{\partial \xi} = f(\xi) > 0} \qquad \text{and} \qquad \boxed{\frac{\partial \sigma_R^2}{\partial \xi} = \frac{2\big[(1 - F(\xi))\, B(\xi) - A(\xi)^2\big]}{A(\xi)^3} > 0},$$

where the strict inequality for σ_R^2 relies on Cauchy–Schwarz: $B(\xi)(1 - F(\xi)) \geqslant A(\xi)^2$ with equality only for degenerate payoffs.

Increasing the cap (higher ξ) raises both left-tail mass and right-tail dispersion; con-

[3] $A(\xi)$ and $B(\xi)$ are standard "truncated moment" objects: $A(\xi) = \int_{\xi}^{\bar{\omega}} (\omega - \xi)\, dF$, $B(\xi) = \int_{\xi}^{\bar{\omega}} (\omega - \xi)^2\, dF$.

versely, **tightening capital regulation** (lower ξ) *reduces both contributions in the same direction*. Thus the variance-cutting effect of stricter capital is "tail-symmetric."

On the other hand, because the cap binds, $\ell = \xi$ is fixed by regulation and does not respond to π:

$$\frac{\partial \xi}{\partial \pi} = 0.$$

Equity pay-offs themselves never contain the bailout transfer, hence

$$\boxed{\frac{\partial \sigma_L^2}{\partial \pi} = 0}, \qquad \boxed{\frac{\partial \sigma_R^2}{\partial \pi} = 0}.$$

A change in the bailout probability π leaves both tails *unchanged* when leverage is already capped. Bailout policy can affect equity-return variance only indirectly—by altering the chosen leverage—once the cap ceases to bind; in that interior region the impact operates through the left tail first and then transmits to the right via the leverage channel.

When the regulatory cap is loose enough that the intermediary's optimal leverage is determined by the first-order condition (G.11), with $\sigma_L^2 = F(\ell^\star)$ I have

$$\boxed{\frac{d\sigma_L^2}{d\pi} = f(\ell^\star)\,\frac{d\ell^\star}{d\pi} \;>\; 0} \qquad \Longrightarrow \qquad \pi\uparrow \;\Rightarrow\; \text{default probability rises.}$$

Using the earlier derivative $\dfrac{\partial \sigma_R^2}{\partial \ell} = \dfrac{2\big[(1-F)\,B - A^2\big]}{A^3} > 0$, the chain rule gives

$$\boxed{\frac{d\sigma_R^2}{d\pi} = \frac{\partial \sigma_R^2}{\partial \ell}\,\frac{d\ell^\star}{d\pi} \;>\; 0} \qquad \Longrightarrow \qquad \pi\uparrow \;\Rightarrow\; \text{right-tail dispersion rises.}$$

Hence, bailouts affect equity variance only through the leverage choice. If the cap is slack, higher π pushes $\ell^\star$ up, thereby raising both the frequency of default (left tail) and the dispersion of surviving returns (right tail). Lower π does the opposite. Tightening ξ that becomes binding compresses leverage directly and symmetrically trims both tails, independent of π.

G.5 Social-planner problem

The planner internalises all real resource costs—dead-weight default losses and equity-issuance costs—while treating bail-out transfers and lump-sum taxes as pure redistribution. Normalising the investment scale to $a = 1$ (linearity), the planner solves

$$\max_{\ell \leqslant \xi} \mathcal{W}(\ell) := \beta \Big[-\underbrace{\phi \int_{\ell}^{\bar{\omega}} (\omega - \ell)\, dF(\omega)}_{\text{equity-issuance cost}} - \underbrace{(1-\chi) \int_{0}^{\ell} \omega \, dF(\omega)}_{\text{default dead-weight loss}} \Big]. \tag{SP}$$

First-order condition. Denote the pdf by $f(\omega) = F'(\omega)$. Differentiating $\mathcal{W}$ and imposing the Kuhn–Tucker multiplier λ^{SP} for the cap constraint:

$$\boxed{\beta\phi\big[1 - F(\ell)\big] - \beta(1-\chi)\,\ell f(\ell) = \lambda^{SP}} \tag{$\mathrm{FOC_{SP}}$}$$

with complementary-slackness $\lambda^{SP}(\ell - \xi) = 0$, $\lambda^{SP} \geqslant 0$. Comparing the $\mathrm{FOC_{SP}}$ with the $\mathrm{FOC_{Priv}}$ in (G.11), I see that the planner internalizes the bailout subsidy as a transfer. Therefore in distress, the planner percived the default costs are higher than the private agent. Because both the marginal benefit is higher and the marginal cost is lower for the intermediary, I have $\ell^{SP} < \ell^{Priv}$ wheneve $\pi > 0$.. Hence the planner faces a classic regulation trade-off: choose ξ low enough to curb excessive leverage (and its dead-weight default losses) yet not so low that it foregoes the efficiency gains from substituting cheaper debt for costly equity. Formally, the optimal capital requirement satisfies

$$\xi^{\star} = \ell^{SP}.$$

G.6 Planner's choice of the bailout probability π

The social planner maximizes total welfare $\mathcal{W}$, which equals the sum of consumer and intermediary utilities. Under risk neutrality, this reduces to minimizing deadweight losses from default and equity costs. I derive the planner's optimal bailout policy in three steps.

Let $\ell(\pi, \xi)$ denote equilibrium leverage under bailout probability π and cap ξ. Welfare per unit asset is:

$$\mathcal{W}(\pi, \xi) = \underbrace{-\beta\phi \int_{\ell}^{\bar{\omega}} (\omega - \ell) dF(\omega)}_{\text{Equity costs}} \underbrace{-\beta(1-\chi) \int_{0}^{\ell} \omega dF(\omega)}_{\text{Default losses}} \tag{G.13}$$

where ϕ captures equity issuance costs and χ recovery rates.

The private FOC for leverage (eq. G.11) equates marginal benefits (subsidy + valuation gap) to marginal costs (default). The social planner internalizes externalities:

$$\ell^{\text{SP}} = \arg\max_{\ell} \mathcal{W}(\ell)$$
$$\Rightarrow \beta[\phi(1 - F(\ell)) - (1 - \chi)\ell f(\ell)] = 0 \tag{G.14}$$

Comparing (G.11) and (G.14) reveals $\ell^*_{\text{Priv}} > \ell^{\text{SP}}$: private leverage exceeds the social optimum due to bailout subsidies. When the cap is slack ($\ell^*_{\text{Priv}} < \xi$), total derivative:

$$\frac{d\mathcal{W}}{d\pi} = \underbrace{\frac{\partial \mathcal{W}}{\partial \ell}\frac{d\ell^*_{\text{Priv}}}{d\pi}}_{\text{Indirect effect via leverage}}$$

$$\text{where } \frac{\partial \mathcal{W}}{\partial \ell} = \beta[\phi(1 - F(\ell)) - (1 - \chi)\ell f(\ell))] < 0 \tag{G.15}$$

$$\frac{d\ell^*_{\text{Priv}}}{d\pi} = \frac{\beta \int_0^{\ell^*} dF + \beta(1 - \chi)\ell^* f(\ell^*)}{(\beta - \beta^{I})f(\ell^*) + \beta(1 - \pi)(1 - \chi)f(\ell^*)} > 0 \tag{G.16}$$

The negative indirect effect dominates, implying $\frac{d\mathcal{W}}{d\pi} < 0$. Thus:

Proposition 2 (Optimal bailout policy)**.** *The welfare-maximizing bailout probability is:*

$$\pi^\star = 0 \quad \textit{(strictly optimal if cap is slack, weakly if binding)}$$

Proof. When ξ binds ($\ell = \xi$), $\frac{d\ell}{d\pi} = 0 \Rightarrow \frac{d\mathcal{W}}{d\pi} = 0$. However, setting $\pi = 0$ remains weakly optimal as bailouts only redistribute without affecting real allocations. For slack caps, the negative leverage effect makes $\pi = 0$ strictly optimal. □