A Q-Theory of Banks*

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We introduce a dynamic bank theory featuring delayed loss recognition and a regulatory capital constraint, aiming to match the bank leverage dynamics captured by Tobin's Q. We start from four facts: (1) book and market equity values diverge, especially during crises; (2) Tobin's Q predicts future bank profitability; (3) neither book nor market leverage constraints are strictly binding for most banks; and (4) bank leverage and Tobin's Q are mean reverting but highly persistent. We demonstrate that delayed loss accounting rules interact with bank capital requirements, introducing a tradeoff between loan growth and financial fragility. Our welfare analysis implies that accounting rules and capital regulation should optimally be set jointly. This paper emphasizes the need to reconcile regulatory dependence on book values with the market's emphasis on fundamental values to enhance understanding of banking dynamics and improve regulatory design.

Keywords: Bank Leverage Dynamics, Market vs. Book Values, Accounting Rules, Bank Regulation, Financial Stability

JEL: G21, G32, G33, E44

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1 Introduction

This paper introduces a banking model that emphasizes the slow recognition of losses in accounting books. Delayed accounting of losses induces a distinction between the fundamental value of equity, which fully incorporates information on losses, and the book value of equity, which does not. This distinction is crucial because bank regulation relies on accounting frameworks while financial vulnerabilities are influenced by fundamental values. Our model underscores the need to consider the limited information in accounting books, both to correctly capture bank behavior and to guide regulatory design.

Our theory is motivated by four stylized facts about banks' leverage and about their ratio of market-to-book equity, which we henceforth call Tobin's Q[1]:

1. **Time series of Tobin's Q:** The banking sector's Tobin's Q fluctuates substantially over time. Market capitalization of banks fell substantially during the 2007/2008 financial crisis, while book equity was stable.

2. **Informational content of Tobin's Q:** Market equity captures information that book equity does not. Tobin's Q predicts bank profits over a two-year horizon and banks' distance to default in the cross-section.

3. **Cross-section of book and market leverage:** Banks hold a capital buffer above the regulatory minimum. Even during the financial crisis, only a small fraction of banks violated their regulatory constraints, and most were well-capitalized according to book measures. In contrast, the dispersion of market leverage (assets over market equity) increased substantially during the financial crisis, and many banks temporarily had very high levels of market leverage.

4. **Dynamic response of leverage and Tobin's Q:** After a net-worth shock, Tobin's Q and market leverage respond on impact and mean-revert slowly. By contrast, book equity does not react on impact but incorporates the shock to net worth gradually.

Fact 1 is that aggregate book equity and market-value equity differ, especially during crises, leading to stark differences in book and market leverage. These measures typically comove in models,[2] but not in the data.[3] However, models must take a stance on whether book or market leverage is constrained, leading to different implications depending on which leverage measure is used to draw inferences.

[1] We refer to the market-to-book *equity* ratio as Tobin's Q, as opposed to the market-to-book *assets* ratio.

[2] Papers that study the asset pricing implications of intermediary net worth (e.g., He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014) use market equity as a state variable, whereas papers that focus on the effects of regulation use book measures of equity (e.g., Adrian and Boyarchenko, 2013; Begenau, 2020; Adrian and Shin, 2013; Corbae and D'Erasmo, 2021; Begenau and Landvoigt, 2022).

[3] See the debate between Adrian, Etula and Muir (2014) and He, Kelly and Manela (2017).

Fact 2 implies that market values contain more information about losses, a feature consistent with many findings in the accounting literature but not with models where book and market measures contain the same information.[4]

Fact 3 regards the cross-sectional dispersion of market and book leverage. Book measures of leverage suggest that banks are almost always well capitalized. Even during the financial crisis, only a small fraction of banks had regulatory capital ratios below the minimum, and the vast majority of banks held a substantial buffer of capital beyond the minimum. In contrast, market-based measures of leverage suggest that leverage rose dramatically during the crisis and that the distribution of leverage also fanned out. As a result, many banks were well capitalized on the books despite significant erosions in their market valuations.[5]

Fact 4 summarizes the dynamics of market and book leverage after net-worth losses. We identify net-worth losses in a panel of US banks by exploiting cross-sectional variation in bank stock excess returns, using a factor model that partials out variation driven by changes in risk premia.[6] We construct time series of bank-level proxies of net-worth shocks from return shocks and estimate the impulse responses of bank variables to those shocks. Fact 4 is that banks adjust very slowly after these shocks.[7] In response to a negative net-worth shock that mechanically increases market leverage, banks reduce their market leverage by slowly reducing their liabilities. Book equity does not respond on impact and declines slowly.

In conjunction, these four facts inform the essential elements of our Q-theory, which is based on a delayed loss accounting mechanism. Our model features a cross-section of risk-neutral banks. Banks fund risky loans with deposits and internal equity. Banks can increase the return on equity by taking on more leverage, capturing frictions that prevent deposits from being properly priced. A regulatory limit and a market-based limit constrain bank leverage. If either limit is exceeded, banks are dissolved and receive a fixed liquidation value. To avoid liquidations, banks optimally maintain a capital buffer.

The key element of our Q-theory is that book equity values differ from fundamental, and hence market, equity value, predominantly because book equity takes time to recognize past loan losses whereas fundamental values contain real-time information on loan losses. Our delayed loss accounting mechanism allows us to decompose Tobin's Q into the ratio of market equity to fundamental equity and *little* q, the ratio of fundamental equity to accounting value equity. When banks face a loan default, their accounting books can momentarily hide the loss. Therefore, while banks hold a capital buffer above the regulatory limit according to their accounting values, their fundamental leverage may exceed the regulatory limit. Banks

[4] Laux and Leuz (2010) explain how banks have flexibility in accounting for losses.

[5] An example is Silicon Valley Bank (SVB), whose equity had been wiped out in market value terms by 2022 Q3 while the bank continued to satisfy capital standards until it was liquidated in March 2023.

[6] It is challenging to identify net-worth shocks because accounting measures do not convey the full extent of losses. Unfortunately, while market values capture more information, they are also affected by variation in aggregate risk premia. Hence, we cannot directly exploit variation in market valuations.

[7] This fact is consistent with the literature on slow-moving capital (Duffie, 2010).

delever slowly, as their losses are slowly recognized on the books. After a net-worth shock, book variables take time to respond, while market leverage reacts instantaneously. These mechanics qualitatively explain all four facts.

We take the model to the data and show that it can also quantitatively explain all four facts. Using US bank-level data, we estimate the discount rates of investors and bankers, a parameter governing dividend-smoothing incentives, the size of loan defaults, a market-based leverage constraint and, importantly, a parameter that governs the speed of loss recognitions, targeting the average growth rate of book equity, the market-to-book ratio of equity, the book leverage ratio, and the impulse responses of market leverage and liabilities to excess-return shocks that proxy net-worth shocks. The estimated model matches the cross-sectional facts well. To match the time series facts, we feed in a sequence of default intensities chosen such that the model matches the historical net charge-off rate after the great financial crisis (GFC).

We embed our Q-theory of banks into a general equilibrium setting to analyze normative implications. In this setting, bank liquidations are socially costly and not internalized by banks. The social cost of liquidations rationalizes the need for capital requirements. However, capital requirements cannot implement the socially optimal leverage. The reason is that, to be effective, violation of capital requirements must involve a penalty—the bank's liquidation. The risk of regulatory liquidations leads to leverage lower than the social optimum; this is a regulatory cost that society must pay to prevent the even costlier excessive risk-taking under unregulated banking.

We employ our Q-theory to analyze regulatory accounting frameworks. We capture different accounting rules through a single parameter, α, which governs the speed of past loan-loss recognitions. This reveals a novel policy tradeoff. On the one hand, more lenient accounting rules prevent banks that suffer losses from deleveraging immediately, which translates into stronger lending. On the other hand, more lenient accounting rules induce banks with large unrecognized losses to take excessive bank liquidation risk. Using the estimated steady state of the model, we compute the socially optimal speed of loan-loss recognition and capital requirements that would maximize welfare during a transition to a new steady state. The optimal policy mix involves a slight relaxation of capital requirements from Basel III to Basel II levels but, importantly, a substantial strengthening of accounting standards toward speedier recognition of loan losses. Hence, a first policy insight is that optimal microprudential policy should shift the emphasis from capital regulation to better accounting standards.

A second policy insight is that delayed accounting has important macroprudential policy implications, namely, for the countercyclical capital buffer (CCyB) introduced in Basel III. When we introduce an aggregate shock to our model with delayed loss accounting, we find that, relative to a benchmark with constant capital requirements, the CCyB can amplify the credit cycle and increase systemic risk. With a temporary relaxation in the capital requirement during a recession, all banks are incentivized to take on excessive risks by increasing leverage during a time of high aggregate risk. As a result, many banks accumulate large amounts of unrealized losses. Once the capital requirement is tightened back to its pre-crisis level, many banks have such high levels of fundamental leverage and unrealized losses that they would rather risk liquidation than lower their leverage levels. The ensuing wave of bank liquidations depletes aggregate equity capital and depresses future loan growth. By contrast, a relaxation in accounting standards during a recession can effectively target only banks hit especially hard by losses, permitting them to reduce leverage more slowly without inducing more risk-taking by unhealthy banks. Taken together, these insights suggest the need to bring accounting rules to the forefront in the design of optimal bank regulation.

Related Literature. Canonical macrofinance models usually employ one concept for equity.[8] Which concept is employed depends on the constraints that intermediaries face. Models motivated by agency frictions place constraints on market values (e.g., Jermann and Quadrini, 2012; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2013).[9] Models with book-based constraints are motivated by questions of regulation (e.g., Adrian and Boyarchenko, 2013; Begenau, 2020; Corbae and D'Erasmo, 2021; Elenev, Landvoigt and Van Nieuwerburgh, 2021; Bianchi and Bigio, 2022).

Relative to this literature, our paper makes three contributions: First, it synthesizes facts about banks' Tobin's Q, shedding light on how market and book equity constrain bank behavior. Second, we build a Q-theory of banks where both market and book equity matter. The theory explains differences in market and book equity through a novel delayed loss accounting mechanism that interacts with regulatory constraints.[10] Third, we conduct policy experiments focused on how reforms to regulatory accounting rules would impact banks and the effectiveness of capital regulation.

There is a large banking and accounting literature on delayed loss accounting incentives and their implications (e.g., Peek and Rosengren, 2005; Caballero, Hoshi and Kashyap, 2008; Blattner, Farinha and Rebelo, 2023; Plosser and Santos, 2018; Flanagan and Purnanandam, 2019).[11] In the macrofinance literature, the effects of accounting rules on bank decisions and

[8]See, e.g., Kiyotaki and Moore (1997); Gertler and Kiyotaki (2010); Gertler and Karadi (2011); Gertler, Kiyotaki and Queralto (2012); Jermann and Quadrini (2012); He and Krishnamurthy (2012); Brunnermeier and Sannikov (2014); He and Krishnamurthy (2013); Gertler and Kiyotaki (2015); Gertler, Kiyotaki and Prestipino (2016); Nuño and Thomas (2017); Piazzesi, Rogers and Schneider (2022).

[9]Examples of such frictions include costly verification (Townsend, 1979; Bernanke and Gertler, 1989), lack of commitment (Hart and Moore, 1994), and moral hazard (Holmstrom and Tirole, 1997).

[10]Slow-moving bank leverage (Fact 4) can also be generated by other models (e.g., Brunnermeier and Sannikov, 2014; Gertler et al., 2016). The differences is that, in those models, the slow leverage dynamics follow from adjustment costs. The Q-theory in this paper delivers slow-moving leverage dynamics through delayed accounting, offering a microfoundation for adjustment costs in other models that differs from leverage-ratcheting incentives (DeMarzo and He, 2021) and debt overhang (Gomes, Jermann and Schmid, 2016).

[11]In Appendix A.2.2, we further detail the bank accounting literature. Bushman (2016) and Acharya and Ryan (2016) offer a nice survey of the literature.

macroeconomic performance are understudied.[12] A notable exception is Milbradt (2012), who studies theoretically the effect of accounting rules on banks' trading behavior.

Our paper contributes to the literature on accounting rules and their effects on financial stability and credit supply.[13] In response to the financial crisis, the procyclical effects of mark-to-market assets were discussed (e.g., Shleifer and Vishny, 2011; Laux and Leuz, 2010; Plantin and Tirole, 2018). Empirical investigations into the enforcement of accounting rules and the impact on bank lending practices appear in Agarwal, Lucca, Seru and Trebbi (2014) and Granja and Leuz (2018), among others. In response to the COVID-19 crisis, the extent of regulatory forbearance took center stage in macroprudential policy discussions (see Blank, Hanson, Stein and Sunderam, 2020). Since the March 2023 banking crisis, there is renewed interest in accounting rules and their ability to conceal risk (e.g., Jiang, Matvos, Piskorski and Seru, 2023; Granja, 2023). To our knowledge, this paper represents the first quantitative exploration of accounting rules and their interplay with regulatory capital constraints. The model here can be used as a framework for assessing both micro- and macroprudential impacts stemming from the implementation of new accounting standards, such as the Current Expected Credit Loss (CECL) accounting standard.[14]

Finally, our paper relates to Corbae and D'Erasmo (2021) and Rios-Rull, Takamura and Terajima (2023) in that bank heterogeneity is an important part of model. The novelty is the focus on how delayed loss accounting induces a cross-sectional distribution of bank leverage that circumvents regulation. This allows us to investigate the joint effects of capital requirements and accounting rules.

2 Motivating Facts

Our Q-theory is motivated by four stylized facts on banks' Tobin's Q and leverage dynamics.

Data. We construct a panel of banks using accounting data—balance sheet and income statements—on US bank holding companies (BHCs) from the FR Y-9C regulatory reports filed with the Federal Reserve from 1990 Q3 to 2021 Q1. We merge the accounting data with market data from the Center for Research in Security Prices (CRSP). See Appendix A.1 for more details on our sample construction and additional results.

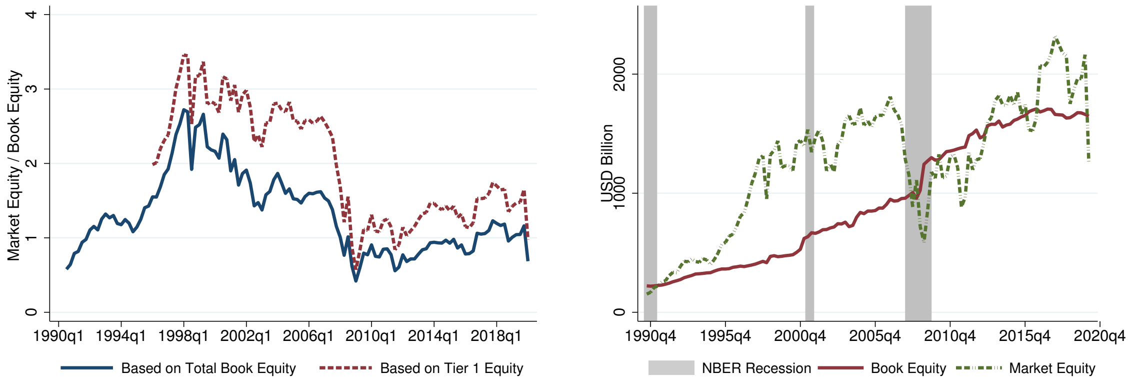
[12]For example, Faria-e Castro, Paul and Sánchez (2024) analyze the economic effects of banks' zombie lending incentives that are not rooted in accounting rules.

[13]There is a related debate on the extent to which capital requirements caused the shift toward shadow banking (e.g., Buchak, Matvos, Piskorski and Seru, 2018; Hachem and Song, 2021; Begenau and Landvoigt, 2022).

[14]For empirical evidence on how CECL accounting rules affect bank lending decisions, see Granja and Nagel (2023) and references therein.

Figure 1: Tobin's Q and Bank Equity Evolution

(a) Tobin's Q (b) Book and Market Equity



Notes: These figures show data on Tobin's Q in Panel (a) and book equity and market equity in Panel (b) for an aggregate sample of publicly traded BHCs. Tobin's Q is the ratio of market equity to book equity and the ratio of market equity to Tier 1 equity capital (only available since 1996). Book equity and Tier 1 equity are from the FR Y-9C. Market equity is from CRSP. Market equity equals shares outstanding times the share price, aggregated across publicly traded BHCs. We exclude new entrants in 2009 such as Goldman Sachs and Morgan Stanley from these aggregate time series. All level variables are converted to 2012 Q1 dollars with the seasonally adjusted GDP deflator.

Motivating Fact 1: There Are Large Differences in Book Equity and Market Equity. Our first fact is that the banking sector's Tobin's Q—the ratio of market equity over book equity—fluctuates widely over time.[15] Panel (a) of Figure 1 shows the time series of Tobin's Q for the aggregate banking sector using two different book equity definitions: total book equity and Tier 1 equity.[16] Panel (b) shows the components of aggregate Tobin's Q across all BHCs. Market valuations often diverge from book valuations, with these discrepancies becoming more pronounced during financial crises. During the 2008/2009 financial turmoil, aggregate book equity remained stable, in stark contrast to market equity, which significantly declined. By 2008 Q4, bank market equity had plummeted over 54% from its 2007 Q3 level, a steeper fall than the 42% drop in the S&P 500 index (numbers are adjusted for inflation with the seasonally adjusted GDP deflator).

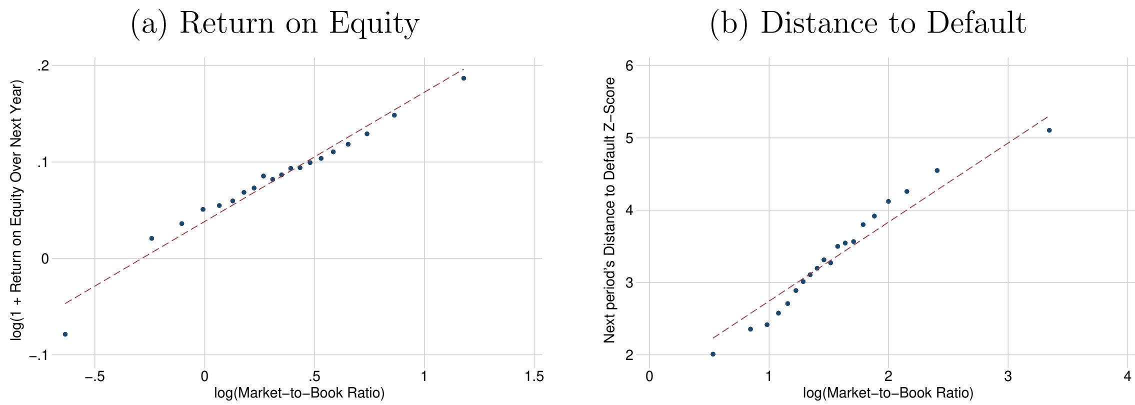
Motivating Fact 2: Tobin's Q Predicts Cash Flows and Default Risk. Our second fact is that Tobin's Q predicts future cash flows, charge-offs, and distance to default (D2D) in the cross-section of banks, suggesting that the market equity value of banks contains information that book equity does not.

Figure 2 illustrates the cross-sectional relationship between banks' log market-to-book

[15]Book and market equity differences during the GFC have been documented before (see, for example, Adrian and Shin, 2010; He et al., 2017). Our paper proposes a theory based on delayed loss accounting as a mechanism to explain the dynamics of bank Tobin's Q.

[16]While the former is available for our entire sample period, Tier 1 capital is a key variable for book regulatory constraints.

Figure 2: More Cash Flow–Relevant Information in Market Than in Book Equity



Notes: This figure presents cross-sectional binned scatter plots of log outcomes on the log Tobin's Q for BHCs. All plots include controls for log book equity as a proxy for size and the Tier 1 capital ratio of each bank and a quarter–time fixed effect. Data on market equity are from CRSP. All other data are from the FR Y-9C reports. Return on equity over the next year is defined as book net income over the next four quarters divided by book equity in the current quarter. The Z-score distance-to-default measure over one quarter is calculated at the bank level as $\frac{\log(V/D)+\mu_V - \frac{1}{2}\sigma_V^2}{\sigma_V}$. V denotes the total value of the bank measured as sum of the market value of equity and the book value of debt. D is measured as the book value of debt, or total liabilities. μ_A is the quarterly growth rate of V. σ_V is the standard deviation of the growth rate of V.

equity ratio and future cash flow, adjusting for time fixed effects, the Tier 1 regulatory capital ratio, and log book equity.[17] Panel (a) demonstrates Tobin's Q as a predictor of next year's log return on equity (ROE), while Panel (b) links it to D2D. Banks with high Tobin's Q are on average further from default and more profitable over the next year. Additionally, Appendix Figure A.2 reveals that banks with high Tobin's Q generally have lower delinquent loan shares and lower future net charge-off rates. These findings suggest that variation in Tobin's Q stems partly from the differing informational content of book and market values.

Book measures are backward looking and record realized losses ex post, while market equity values capture current and future expected cash flows. Time series variation in Tobin's Q could also indicate discount rate movements, but this is unlikely in our cross-sectional analysis. Instead, the ability of Tobin's Q to forecast future accounting cash flows in the cross-section points to a delay in the recognition of cash flow shocks in accounting values.

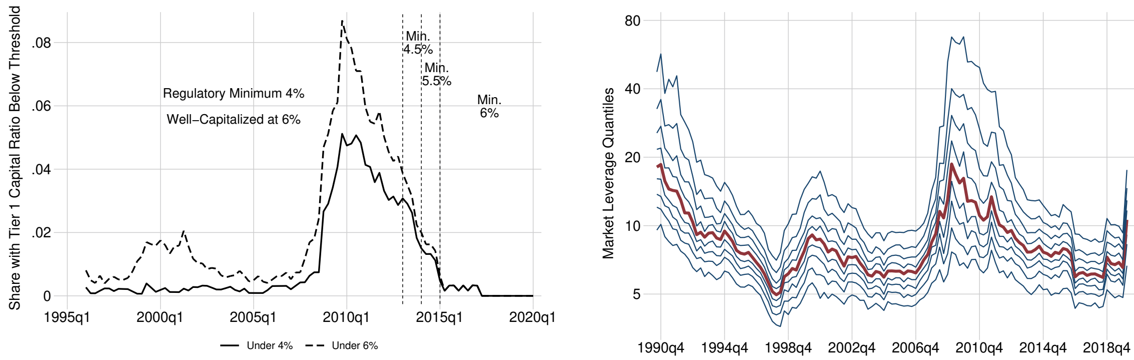
Motivating Fact 3: Regulatory Constraints Are Rarely Strictly Binding, and Market-Based Leverage Fans out During Crises. Our third stylized fact clarifies the nature of banks' leverage constraints. Panel (a) of Figure 3 presents the fraction of banks whose Tier 1 capital ratio falls below different cutoff values near the regulatory constraint; Appendix A.2.1 discusses how capital requirements have changed over time. The vast majority of banks keep a capital buffer above the required minimum. Even at the height of the

[17] To control for covariates, we residualize the left- and right-hand-side variables on the controls and then add back the mean of each variable to maintain the centering. It is important to control for log book equity to prevent spurious results due to ratio bias (see Kronmal, 1993).

financial crisis, over 90% of banks were "well capitalized" according to their Tier 1 capital ratio, and only 5% were below the regulatory minimum. Consistent with delayed recognition of loan losses, the share of banks near the regulatory limit peaked only by the first quarter of 2010, two years after the crisis began.

Figure 3: Leverage Constraints

(a) Regulatory Constraints (b) Market Leverage Quantiles



Notes: This figure shows the distribution of bank holding companies constrained by capital requirements in Panel (a) and the quantiles of market leverage in Panel (b) for BHCs on a log scale. Panel (a) plots the share of banks whose regulatory Tier 1 capital ratio, defined as (Tier 1 Capital)/(Risk-Weighted Assets), falls below a given threshold, computed from the full, unweighted sample. The regulatory capital requirements are shown on the graph and described in the text. Book data (liabilities) come from the FR Y-9C, and market equity data are from CRSP. In Panel (b), market leverage is computed as (Liabilities + Market Equity)/Market Equity. The median value is plotted in bold red. Each tenth percentile is plotted in the thin blue lines.

Panel (b) of Figure 3 plots quantiles of the market leverage distribution over time. The median is plotted as a bold red line, and other deciles are plotted as thinner blue lines. Market leverage rose during each episode of banking stress: during the savings and loan crisis (1990–1991), during the financial crisis (2008–2009), and at the onset of the COVID-19 pandemic (2020–2021). The cross-sectional distribution of market leverage widened during these episodes. Between 2006 Q4 and 2009 Q1, the 90th percentile of market leverage rose nearly eightfold, from 8.5 to 67, while the median percentile rose only from 5.2 to 17.7. This pattern is inconsistent with binding market leverage constraints during a crisis. If market leverage constraints were binding, we would expect a widespread loan default event to result in a compression of the market leverage distribution as more banks hit the constraint. However, Panel (b) shows an increase in this dispersion, in contrast to the expected compression due to bunching at the constraint.[18]

The distribution of bank leverage differs notably from that of nonfinancial firms. As shown in Appendix Figure A.7, market and book leverage are much lower and less dispersed

[18]Figure A.3 in Appendix A.2.4 shows the distribution of book leverage over time: it is much less dispersed and stabler over time than the market leverage distribution.

for nonfinancial firms than for banks. The literature has rationalized the stark contrast between banks' and nonfinancial firms' leverage levels with liquidity services providing deposits and bank government guarantees not extended to nonfinancial firms. Banks' incentive to carry high leverage, potentially in excess of the social optimum, and regulatory constraints on bank leverage are two critical components that distinguish our model of banks in Section 3 from models of nonfinancial firms.

Motivating Fact 4: Leverage Dynamics Are Slow. Our fourth and final fact is that banks adjust slowly in response to idiosyncratic shocks. This creates a prolonged gap between their market and book equity, impacting Tobin's Q. Market leverage is also slow to revert to pre-shock levels, with the adjustment driven primarily by a change in liabilities rather than a recovery in market equity. We show this empirically using a distributed-lag model (e.g., Kilian, 2009) to represent changes in the bank's outcome variable $y_{i,t}$ as a function of a net-worth shock $\varepsilon_{i,t}$:

$$\Delta \log(y_{i,t}) = \alpha_t + \sum_{h=0}^{k} \beta_h \cdot \varepsilon_{i,t-h} + \psi_{i,t}, \tag{1}$$

where i indexes banks, t indexes quarters, k is the estimation horizon,[19] the outcome is $\Delta \log(y_{i,t}) = \log(y_{i,t}) - \log(y_{i,t-1})$, α_t is a time fixed effect, $\varepsilon_{i,t}$ denotes the net-worth shock (defined in the next paragraph), and $\psi_{i,t}$ is an estimation error term. Given a shock $\varepsilon_{i,t}$, Equation (1) allows us to construct impulse-response functions (IRFs) for Tobin's Q and other bank outcome variables of interest. By including time fixed effects, we isolate idiosyncratic from aggregate shocks and recover partial-equilibrium IRFs estimated from the cross-sectional variation in shocks. To report the IRFs, we sum the coefficients cumulatively to trace out the response to a unit shock in $\varepsilon_{i,t}$. That is, the IRF is defined as

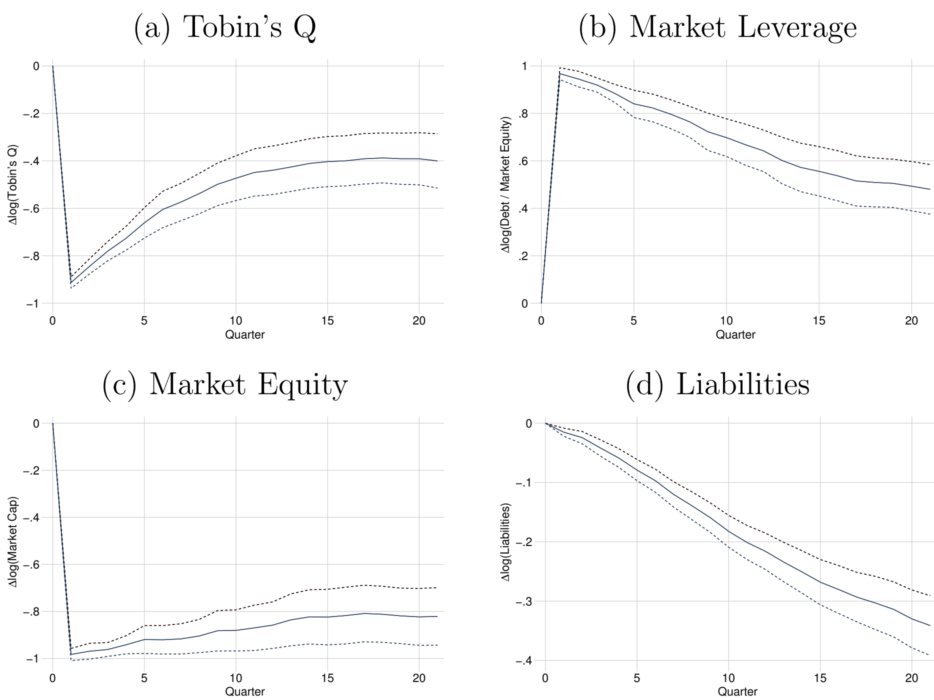
$$\mathrm{E}_t\left[\log(y_{i,t+k}) \,|\, \varepsilon_{i,t} = 1\right] - \mathrm{E}_t\left[\log(y_{i,t+k})\right] = \sum_{h=0}^{k} \beta_h.$$

We interpret the shocks, $\varepsilon_{i,t}$, as idiosyncratic shocks to the bank's net worth, reflecting changes in expected cash flows. In our model, we show that these shocks follow from loan defaults. To estimate these net-worth shocks, we use shocks to banks' excess stock returns—see Appendix Section B.1. The main idea is based on the efficient-markets hypothesis: after adjustment for risk-premia, excess returns are ex ante unpredictable. Cross-sectional variation in $\varepsilon_{i,t}$ then represents unanticipated shocks that perturb bank equity. Our main empirical challenge is to empirically identify these shocks, $\varepsilon_{i,t}$, and isolate them from shocks to (a) the discount rate (risk premia) or (b) future investment opportunities.

[19] In all specifications, we set $k = 20$.

To remove discount rate shocks, we decompose each bank's log excess stock return into an idiosyncratic component and a factor component by estimating a five-factor model for each bank as in Gandhi and Lustig (2015).[20] This isolates idiosyncratic, risk-adjusted return shocks for each bank, akin to the procedure in Vuolteenaho (2002). We then use these estimated return shocks, $\hat{\varepsilon}_{i,t}$, as instruments for the bank's log stock returns, in a model analogous to Eq. (1).[21] We conduct a variety of robustness checks to validate our identification strategy in Appendix Section B.3.

Figure 4: Estimated Impulse Responses



Notes: These figures show the estimated percent impulse responses to a 1% negative return shock. The y-axis of our plots shows the contemporaneous response ($-\beta_0$) as quarter 0, the cumulative response one quarter later ($-\beta_0 - \beta_1$) as quarter 1, and so on. Dashed lines denote the 95% confidence interval. Standard errors are clustered by bank. The panels display the impulse responses of a change in log Tobin's Q in Panel (a), change in log market leverage in Panel (b), change in log market equity in Panel (c), and change in log liabilities in Panel (d). Market leverage is defined as (Liabilities/Market Capitalization). The sample is publicly traded BHCs from 1990Q3 to 2021Q1 using FR-Y-9C and CRSP data.

Figure 4 presents the IRFs to a negative 1% return shock. The key takeaway is that banks adjust very slowly. Panel (a) shows that a 1% negative return shock lowers Tobin's Q by approximately 0.9% on impact, with a partial recovery over the next four years. The shock affects the components of Tobin's Q, market equity and book equity, differently. Market equity falls immediately by approximately 1% on impact and recovers to -0.8% after four years, remaining stable thereafter (see Panel (d) in Appendix Figure A.4). In Panel (c), book

[20] These five factors are the three Fama–French factors (Fama and French, 1993), a credit factor calculated as the excess return on an index of investment-grade corporate bonds, and an interest rate factor calculated as the excess return on an index of 10-year US Treasury bonds.

[21] In Appendix Section B.1, we prove that this consistently estimates the coefficients of the true model.

equity declines slowly, reaching -0.5% only after 10 quarters. These results imply that net worth shocks that are immediately recognized in market equity are only slowly recognized on banks' books. The responses of bank market leverage and liabilities, in Panels (b) and (d), also suggest a slow adjustment process. In response to a negative net-worth shock, banks delever by slowly paying off liabilities. In sum, cash flow shocks drive a long-lasting wedge between the market and book valuations of banks and also drive gradual adjustment dynamics in leverage.

Appendix A.3 presents the stylized facts using data from publicly traded nonfinancial firms. We find that some of the facts (Facts 2 and 4) are similar among nonfinancial firms whereas others (Facts 1 and 3) are not. The fact that accounting values are slow to incorporate losses in nonfinancial firms is not surprising given that delayed loss accounting rules affect nonfinancial firms as well. The key difference between banks and nonfinancials that we focus on is the fact that banks are much more debt financed than nonfinancials and that banks face regulatory constraints in terms of book values, inducing an *interaction* between book-based accounting rules and regulatory leverage constraints.

3 Q-Theory

This section presents our Q-theory of banks. We embed this banking block into a general equilibrium setting when we discuss the normative implications. Proofs and further details are found in the appendix.

3.1 Model

Environment. Time is indexed by $t \in [0, \infty)$. All assets are real. A continuum of banks fund loans, $L \geq 0$, with deposits, $D \geq 0$, and equity, $W \equiv L - D$. The demand for loans and supply of deposits are perfectly elastic at the rates r^L and r^D, respectively.

Bank Objective. Each bank maximizes the expected discounted value of future dividends:

$$V_0 = \mathbb{E}\left[\int_0^\infty \exp\left(-\rho t\right) C_t ds\right],$$

where C_t denotes dividends at instant t and $\rho > 0$ is the discount rate. Banks follow a constant dividend rate rule, $C_t = cW_t$. In the quantitative section, banks choose the dividend rate, but this is an inessential feature introduced only for calibration purposes.

Loan Defaults and Portfolio Decision. Loan defaults are the only risk banks face. Defaults are i.i.d. across banks and arrive according to a right-continuous (or càdlàg) Poisson process dN, with intensity σ. When the shock arrives, a fraction ε of L will default.

At each instant, banks choose leverage $\lambda \geq 1$, with $L = \lambda W$ and $D = (\lambda - 1) W$. Equity satisfies the following stochastic-differential equation:

$$dW = \underbrace{\left[\underbrace{r^L \lambda - r^D (\lambda - 1)}_{\text{ROE}} - c \right] W}_{\equiv \mu^W W} dt - \underbrace{\underbrace{\varepsilon \lambda W}_{\text{default loss}}}_{\equiv J^W W} dN. \tag{2}$$

Equity features a scaled drift, μ^W, which increases with the ROE and decreases with the dividend rate c. Equity losses occur upon a default, appearing in the scaled equity jump term J^W. Importantly, equity losses scale with λ.

Notation. For a level variable x, we use $\mu^x W$ to denote the drifts scaled by equity and $J^x W$ to refer to its jump scaled by equity. When a variable x is a ratio, the scaling is unnecessary—μ^x and J^x denote unscaled drifts and jumps. Below, we distinguish between book and fundamental values, denoting by $\bar{X}$ the book value of fundamental variable X. We use calligraphic letters to represent economy-wide aggregates: e.g., $\mathcal{L}$ represents the aggregate stock of loans.

Equity Definitions, Accounting Rules, and Zombie Loans. We distinguish three forms of equity: the fundamental value encountered above, W; the book (or accounting) value, $\bar{W}$; and the market value, S. Book equity $\bar{W}$ differs from fundamental equity W. Whereas fundamental equity immediately reflects defaults, book values record losses with a lag.

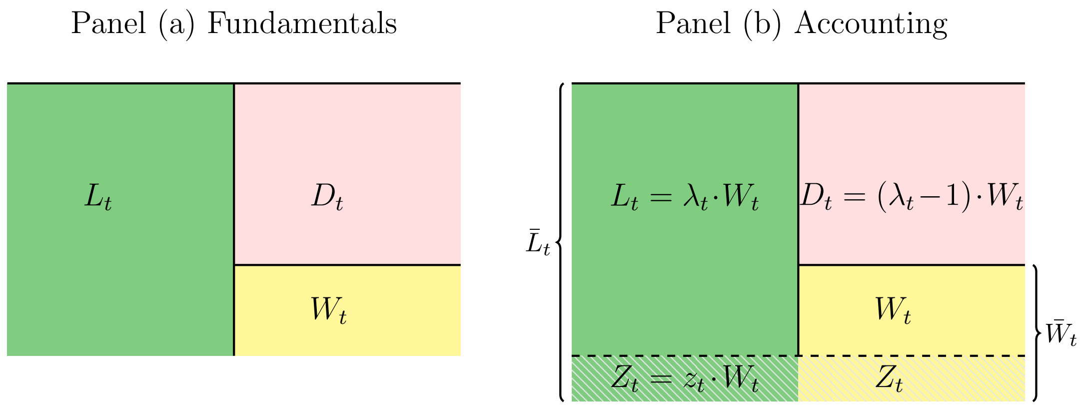
Book equity is relevant because regulation is based on accounting books. The gap between fundamental and book equity is given by the stock of unrecognized defaults Z, which we call zombie loans. On the books, loans appear as the sum of fundamental loans plus zombie loans Z, $\bar{L} \equiv L + Z$. Thus, book equity includes zombie loans as well, $\bar{W} \equiv \bar{L} - D = W + Z$. We label the stock of unrecognized losses as zombie loans because they survive as loans on the accounting books but are "dead" and will not yield payments.

Figure 5 sketches the bank's fundamental balance sheet (Panel (a)) and accounting balance sheet (Panel (b)). On the books, zombie loans are part of the stock of book loans and book equity. We define the zombie loan ratio, $z \equiv Z/W$, as the ratio of zombie loans to fundamental equity. Book leverage is $\bar{\lambda} \equiv \bar{L}/\bar{W} = (\lambda + z) / (1 + z)$. As is clear from the figure, banks seem less levered on the books when the zombie ratio is higher.[22]

While fundamental and book equity differ by the amount of zombie loans, fundamental equity W and market equity S differ when shareholders' discount rate ρ^I differs from the

[22] $\lambda - \bar{\lambda} = (\lambda - 1) z / (1 - z) \geq 0$ is increasing in z.

Figure 5: Fundamental and Accounting Balance Sheet



Notes: This figure shows the balance sheet of the bank in terms of fundamental values (Panel (a)) and book values (Panel (b)).

return on equity.[23] We articulate a notion of market-based equity to decompose Tobin's Q, defined in the usual sense as $Q \equiv S/\bar{W}$, into the product of two ratios:

$$Q \equiv \frac{S}{W} \cdot q, \tag{3}$$

the market-to-fundamental value S/W and the ratio of fundamental equity to book equity or little $q \equiv W/\bar{W} = 1/(1+z)$, the novel feature of our theory. We use our measure of market-based equity to construct model-based IRFs, as we did with the data. Whereas book equity and market equity have data counterparts, the fundamental value does not.

Informational Assumptions and Timing of Liquidations. Banks face the possibility of market and regulatory liquidations. Market discipline induces liquidations if fundamental leverage λ exceeds an upper bound κ. Regulators dissolve banks if their book leverage exceeds a regulatory limit Ξ. Thus, banks are liquidated if at any instant t they violate either of the following constraints:

$$L/W \leq \kappa \quad \text{or} \quad \bar{L}/\bar{W} \leq \Xi. \tag{4}$$

If banks are liquidated, bankers recover an exogenous fraction v_0 of the fundamental equity. A liquidated bank is replaced by a new bank that starts with $z = 0$ and the remaining equity of the liquidated bank.

We combine the inequalities in (4) into a single constraint in terms of λ and z:

$$\lambda \leq \Gamma(z) \equiv \min\{\kappa,\ \Xi + (\Xi - 1)\, z\}. \tag{5}$$

[23]The shareholder values the bank based on its stream of dividend payments. If leverage, and thus the return on equity, are constant, then this yields the valuation $\frac{C}{\rho^I - (\text{ROE} - C)} \cdot W$ via the Gordon growth formula. This will equal W only if $\text{ROE} = \rho^I$.

We label $\Gamma(z)$ the *liquidation boundary.* If at any instant $\lambda > \Gamma(z)$, the bank is liquidated. Regulation is more stringent than the market-based constraint if $z < z^m \equiv (\kappa - \Xi) / (\Xi - 1)$.

Banks never choose to be liquidated voluntarily by setting their leverage above the liquidation boundary. However, banks face involuntary liquidations because their loans are risky and banks do not control their leverage at the moment of a loan default. We assume that investors have real-time information on the bank's fundamental and accounting variables. Thus, they are perfectly informed about the state variables of the bank, W and Z. Hence, at the moment of a default event, a bank with leverage λ is liquidated by market discipline if the following condition is violated:

$$\underbrace{\frac{\overbrace{\lambda W - \varepsilon\lambda W}^{\text{loans after default}}}{\underbrace{W - \varepsilon\lambda W}_{\text{equity after default}}}}_{\equiv \lambda + J^{\lambda}} \leq \kappa. \tag{6}$$

Because fundamental leverage jumps to $\lambda + J^{\lambda}$ at the moment of a default, leverage may violate (4). If the bank survives the default episode, it can reverse the jump in leverage by selling part of its loans immediately after the event.

Market-induced liquidations occur because banks cannot always immediately offset the jump in leverage by selling assets. In technical terms, leverage is nonadaptive—it jumps at the instant of a default event and then reverts. This is the analogue of a discrete-time setting where leverage is a beginning-of-period choice but a random shock at the end of the period alters its value.

The public nature of market prices implies that regulators can infer W and Z. Therefore, markets and regulators share the same information set. Critically, however, regulators cannot enforce regulation on the basis of market values, even though they can perfectly infer Z from market values. Regulation can lead to bank liquidations only if bank accounting values show proof of regulatory noncompliance.

While banks can hide losses on their books, they still face the risk of regulatory liquidations. This is because banks cannot hide losses instantaneously. We assume that, at the moment of default, regulators can use the equity loss $\varepsilon\lambda W$ as evidence if they intervene. We assume that regulators intervene in a bank and demonstrate lack of compliance whenever the bank is provably violating the regulatory limit. Thus, banks are liquidated if the following condition is violated:

$$\underbrace{\frac{\overbrace{\bar{L} - \varepsilon\lambda W}^{\text{book loans after default}}}{\underbrace{\bar{W} - \varepsilon\lambda W}_{\text{book equity after default}}}}_{\equiv \bar{\lambda} + J^{\bar{\lambda}}} \leq \Xi. \tag{7}$$

If the bank survives the default event without regulatory liquidation, it can conceal its loss by adding it to the stock of zombie loans the instant after the loan default event. Once these losses are concealed as zombie loans, regulators cannot use them as evidence of noncompliance. Moreover, since hiding losses relaxes the bank's constraints in the future, the bank will always choose to hide losses. Thus, zombie loans jump immediately after each default event survived by the bank. As a result, Z_t is also a nonadaptive process. We discuss the motivation for our informational assumptions in greater detail below.

If regulators were oblivious to bank losses, Eq. (7) would not include default losses and Z_t would be adaptive. As we show in Appendix E.1, banks would face only the risk of market-based liquidations but would not be affected by the regulatory constraint and would not keep a regulatory buffer. We describe the timing and stochastic processes corresponding to each model variable in greater detail in Appendix D.1.

Shadow Boundary. The *shadow boundary* is a key object in our model. For a given z, the shadow boundary $\Lambda(z)$ is the maximum leverage such that the bank survives a default shock:

Lemma 1 *[Shadow Boundary] A bank satisfies the survival conditions (6)–(7) if and only if $\lambda \leq \Lambda(z)$ where:*

$$\Lambda(z) = \min\left\{\frac{\Xi + (\Xi - 1)z}{1 + (\Xi - 1)\varepsilon}, \quad \frac{\kappa}{1 + (\kappa - 1)\varepsilon}\right\}.$$

$\Lambda(z) = \kappa / (1 + (\Xi - 1)\kappa)$ *when* $z \geq z^s \equiv \frac{1-\varepsilon}{1-\varepsilon+\varepsilon\kappa} \times \frac{\kappa - \Xi}{\Xi - 1} = \frac{1-\varepsilon}{1-\varepsilon+\varepsilon\kappa} \times z^m$.

The formula for $\Lambda(z)$ shows that a larger z allows banks to lever up safely, avoiding regulatory liquidations up to the point where z reaches z^s. When $z > z^s$, the shadow boundary is flat because the market-based constraint is the relevant margin. Figure 6 depicts an example of a pair of shadow and liquidation boundaries. The figure also depicts how a bank starting from a leverage and zombie loan ratio pair $u = \{\lambda, z\}$, above the shadow boundary, jumps to u' above the liquidation boundary after default. That bank would be liquidated. We return to this figure to describe the dynamics when banks survive.

Evolution of Zombie Loans. Zombie loans evolve according to the left-continuous process:

$$dZ = \underbrace{\underbrace{-\alpha Z \cdot dt}_{\text{loss recognition rate}}}_{\equiv \mu^Z \cdot W} + \underbrace{\underbrace{\varepsilon \lambda W \cdot dN}_{\text{unrecognized default}}}_{\equiv J^Z W}, \tag{8}$$

where $\alpha > 0$ is meant to capture the speed of loan loss recognition. Zombie loans jump by the amount of losses the instant *after* default events. α reflects accounting rules and regulatory procedures that affect the speed of loan loss recognition. We pay special attention to how

α governs the dynamics of bank variables, allowing us to match the data and show how it affects welfare.

The zombie loan ratio z has a law of motion:

$$dz = -\underbrace{z\left(\alpha + \mu^{W}\right)}_{\equiv \mu^z} dt + \underbrace{\lambda\varepsilon\left[\frac{1+z}{1-\lambda\varepsilon}\right]}_{\equiv J^z} dN. \tag{9}$$

z decreases with α and the equity growth rate μ^W and jumps upon a default event.

Bank's Problem. The bank's state variables are $\{Z, W\}$, and it controls λ and solves a Hamilton–Jacobi–Bellman (HJB) equation:

Problem 1 *[Bank's Problem] The bank's optimal leverage $\{\lambda(Z, W)\}$ solves:*

$$\begin{aligned} \rho V(Z, W) &= \max_{\lambda \in [1, \Gamma(Z/W)]} cW + V_Z(Z, W)\,\mu^Z W + V_W(Z, W)\,\mu^W W \\ &+ \sigma \underbrace{\left[V\left(Z + J^Z, W + J^W\right) - V(Z, W)\right]}_{\text{jump in value after loan default}} \end{aligned} \tag{10}$$

subject to the law of motion of fundamental equity, (2), the law of motion of zombie loans, (8), and the liquidation condition, $V\left(Z + J^Z, W + J^W\right) = v_o W$ if $\lambda > \Lambda(z)$.

Throughout the paper, the market value of equity, $S(Z, W)$ solves the same HJB equation, but with ρ^I replacing ρ, the bank's leverage choice taken as given, and assuming shareholders are wiped out when the bank is liquidated. For the rest of paper, we assume:

Assumption 1

1. *Lending is profitable: $r^L - \sigma\varepsilon \geq r^D$.*
2. *Returns are bounded: $\rho > r^D + \left(r^L - r^D\right)\kappa - c$.*
3. *Liquidation is costly for self-financed banks: $\left(\rho - r^L\right) v_o / c \leq 1 - \varepsilon$.*
4. *If indifferent between risking and not risking liquidation, the bank chooses to avoid liquidation.*

The first condition guarantees that lending is profitable. The second bounds equity growth. The third guarantees that banks avoid liquidation for tight constraints but risk liquidations otherwise. The fourth condition implies that banks avoid risking liquidations unless they have a strictly positive benefit from doing otherwise.

Discussion of Model Assumptions. Our model features several financial frictions. First, in line with the intermediary asset pricing literature (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014), bank equity grows only through retained earnings. Second, depositors do not price bank liquidation risk, a friction capturing the existence of deposit insurance (Diamond and Dybvig, 1983) or implicit government guarantees (Kelly, Lustig and Van Nieuwerburgh, 2016; Atkeson, d'Avernas, Eisfeldt and Weill, 2018). Finally, the regulatory leverage constraint (5) and the implicit liquidation costs limit deposit funding. These last two ingredients depart from standard corporate finance models and make this model specific to banks.[24] In the normative analysis, we introduce social liquidation costs.

Delayed loss accounting, the novel feature of our model, captures a bank's ability to engage in evergreening (Caballero, Hoshi and Kashyap, 2008) and avoid immediate recognition of market losses (Flanagan and Purnanandam, 2019). By delaying charge-offs, banks create zombie loans, avoiding reductions in regulatory capital. Since rolling over a loan does not require new funds, evergreening allows a bank to freely inflate its accounting equity. The effect is to relax the leverage constraint (5). The assumption that losses cannot be hidden instantaneously reflects that evergreening requires renegotiation of a loan, which may take time. Likewise, moving assets from market- (fair-) value accounts to hold-to-maturity accounts may take accountants and financial officers some time.

That investors have real-time knowledge of the bank's fundamentals aligns with the empirical findings in Section 2 suggesting that Tobin's Q contains more predictive power than book values. This fact could be driven by analysts forecasting a bank's loan portfolio defaults based on sources other than the bank's books.[25]

A critical assumption is that regulators cannot close banks on the basis of market data alone. To do so, they must intervene in the bank and provide evidence of noncompliance. This assumption is grounded in the legal constraints faced by regulators. In principle, regulators could constantly intervene, preventing banks from hiding their losses. Hence, we also need to assume that regulators intervene only when they know, from prices, that the bank is in violation of its regulatory constraint. This assumption seems reasonable given that regulatory interventions entail fiscal costs and unwarranted interventions carry the risk of provoking a regulatory backlash.

Appendix D.8 presents a simple sequential-form game based on costly state verification, in the spirit of Townsend (1979), consistent with this discussion.[26] These informational and

[24] Appendix D.6 clarifies this point by relating conditions (6)–(7) to financial solvency.

[25] An alternative assumption is that prices convey information only when banks are in critical condition. Market signals may be noisy because of trader noise or discount rate shocks, all elements outside the model. However, market signals may be strong for noncompliant banks. For example, if a bank's leverage surpasses a regulatory limit, its market value may collapse, leading to a self-fulfilling intervention.

[26] Taking the $\Delta \to 0$ limit of this game provides a microfoundation for the timing of regulatory liquidations in the model. We thank Douglas Diamond for making a connection with these models.

timing assumptions mirror the events of the regional banking crisis in 2023.[27]

3.2 Positive Analysis

We now present the solution to the bank's problem. We start with immediate accounting to explain the inherent risk–return tradeoff.

Immediate Loan Loss Recognition. Immediate loan loss recognition occurs when $\alpha \to \infty$ and $z_t = 0, \quad \forall t$. Consider the *laissez-faire regulation* where $\kappa < \Xi$. In this case, under immediate loss recognition, the shadow and liquidation boundaries simplify to constants, $\Gamma = \kappa$ and $\Lambda = \kappa \cdot (1 + \varepsilon(\kappa - 1))^{-1}$, respectively.

Proposition 1 *[Immediate Accounting Solution] With immediate accounting, $V(0, W) = vW$ and $L = \lambda^* W$, where $v = c(\rho - (\Omega^* - c))^{-1}$, Ω^* is the optimal expected levered equity return,*

$$\Omega^* = r^D + \max_{\lambda \in [1,\kappa]} \underbrace{\underbrace{\left(r^L - r^D\right)}_{\text{levered return}} \lambda + \sigma \left\{ (1 - \varepsilon\lambda) \mathbb{I}_{[\lambda \leq \Lambda]} + \frac{v_o}{v} \mathbb{I}_{[\lambda > \Lambda, \lambda \leq \kappa]} - 1 \right\}}_{\text{portfolio objective } \equiv \Omega(\lambda)}, \tag{11}$$

and λ^* is the optimal leverage in Ω^*.

This analysis yields three takeaways that carry through to the general case. First, the bank's problem scales with W. Second, the marginal value of bank equity, v, converts a unit of W into an anticipated net present value of dividends. Third, selecting the optimal leverage maximizes the expected return on equity Ω^*. This maximization balances a tradeoff between levered returns and liquidation risk.

If the bank sets $\lambda > \kappa$, it is immediately liquidated. Hence, $\lambda \in [1, \kappa]$. The objective function $\Omega(\lambda)$ in (11) is increasing in λ except at a discontinuous drop located at the shadow boundary Λ. This drop occurs because, when leverage exceeds the shadow boundary, the bank risks liquidation.[28] Since the objective is piecewise linear, with a discontinuity, optimal leverage is either at the shadow or the liquidation boundary:

$$\Omega^* = r^D + \max \left\{ \overbrace{\left(r^L - r^D\right)\kappa - \sigma\left(1 - \frac{v_o}{v}\right)}^{\text{liquidation boundary}}, \quad \overbrace{\Lambda\left(\left(r^L - r^D\right) - \varepsilon\sigma\right)}^{\text{shadow boundary}} \right\}.$$

[27]Notably, they mirror the dissolution of SVB in 2022 Q3. Despite being insolvent, the bank remained solvent under book-based regulatory standards. This disconnect resulted from held-to-maturity securities being valued at their amortized costs rather than their diminished fair value. This discrepancy allowed a significant portion of SVB's securities holdings to appear inflated and meet regulatory standards. The regulator acted only after the bank's stock valuation had plummeted.

[28]In Appendix D.5, we further discuss and plot the objective function in $\Omega(\lambda)$.

A parametric condition dictates which of the two corners is optimal.

Corollary 1 *Let λ^o be the unique (positive) solution to:*

$$\overbrace{\left(r^L - r^D\right)\left(\lambda^o - \frac{\lambda^o}{1+\varepsilon\left(\lambda^o - 1\right)}\right)}^{\text{difference in levered return}} = \sigma \overbrace{\left(1 - \frac{v_o}{v} - \varepsilon \frac{\lambda^o}{1+\varepsilon\left(\lambda^o - 1\right)}\right)}^{\text{difference in expected losses}}. \tag{12}$$

Optimal leverage is at the liquidation boundary, $\lambda^* = \kappa$, if $\kappa > \lambda^o$. Otherwise, optimal leverage is at the shadow boundary, $\lambda^* = \Lambda$.

The significance of the result is that banks risk liquidations, setting leverage to the liquidation boundary, when leverage is permitted to be high enough. This is because the levered return scales with leverage but liquidation recovery values are independent of leverage. If leverage is not permitted above a threshold, banks set their leverage to the shadow boundary, sacrificing returns but guaranteeing continuation.

Away from laissez faire, regulation is binding. In this case, with immediate accounting, the solution is isomorphic to the laissez-faire case, except that κ is replaced by the regulatory constraint Ξ. Thus, the optimal leverage, as outlined in Corollary 1, generalizes to:

$$\begin{aligned} \lambda^*\left(\Xi, \kappa\right) &= \min\left\{\kappa, \Xi\right\} \times \mathbb{I}_{\left[\min\left\{\kappa, \Xi\right\} > \lambda^o\right]} \ldots \\ &+ \min\left\{\kappa, \Xi\right\}\left(1 + \varepsilon\left(\min\left\{\kappa, \Xi\right\} - 1\right)\right)^{-1} \times \mathbb{I}_{\left[\min\left\{\kappa, \Xi\right\} \leq \lambda^o\right]}. \end{aligned} \tag{13}$$

This bang-bang property carries through to the general case with delayed accounting.

Dynamics with Immediate Loss Recognition Accounting Rules. Under immediate loss recognition, the model has no internal propagation: banks instantly offset leverage changes via asset sales, leading to a single jump in the IRFs of total liabilities and book equity. Moreover, Tobin's Q is constant, as little q (the ratio of fundamental to book equity) is always one. Thus, Q lacks predictive power. Immediate accounting also eliminates cross-sectional variation in leverage ratios. The version of the model with immediate loan loss recognition is inconsistent with several of the facts presented in Section 2.

A common approach to producing variation in Tobin's Q and more sluggish adjustments of bank variables is to introduce balance sheet adjustment costs. Suppose we solved a variation of our model with adjustment costs and immediate accounting. This could generate a slow response of leverage, as in Fact 4, but would not cause losses to be predictable with Tobin's Q, as in Fact 2. This is because all losses would be immediately recorded on the books and so Tobin's Q should have no predictive power for ROE or charge-offs once we control for book equity. In an earlier version of this paper, we estimated an alternative version of the model that featured balance sheet adjustment costs and delayed accounting without economic bite because capital requirements were stated in terms of fundamental values. That model required implausibly large adjustment costs to explain the slow dynamics of leverage. Our delayed accounting mechanism provides a more plausible microfoundation for a "reduced-form" adjustment cost, such that we need not rely on the actual adjustment costs that the bank must pay.

Delayed Accounting. We now characterize the solution under delayed accounting.

Proposition 2 *[General Solution] With delayed accounting, $V(Z,W) = v(z)W$ and $L(Z,W) = \lambda^*(z)W$ where:*

$$\rho v(z) = c - v_z \cdot \alpha \cdot z + (v(z) - v_z(z)z) \cdot \Omega^*(z), \tag{14}$$

and $\lambda^*(z)$ solves:

$$\Omega^*(z) = r^D + \underbrace{\max_{\lambda \in [1,\Gamma(z)]]} \left(r^L - r^D\right)\lambda + \sigma\left\{\frac{J^v(z,\lambda)}{v(z) - v_z(z)z}\right\}}_{\Omega(z,\lambda) \quad \textit{leverage choice}},$$

where $J^v(\lambda, z) \equiv v(z + J^z)(1 - \varepsilon\lambda)\mathbb{I}_{[\lambda \leq \Lambda(z)]} + v_0\mathbb{I}_{[\lambda > \Lambda(z)]} - v(z)$.

With delayed accounting, the bank's problem is also scale invariant: two banks with the same z behave as W-scaled replicas. The key difference is that z determines the shadow and liquidation values. For this reason, the valuation of equity $v(z)$ depends on z. The term $v(z) - v_z(z)z$ that multiplies the levered portfolio captures how an increase in equity increases the value of the bank directly and indirectly through z.

In this case, the choice of leverage depends on z, as shown next:

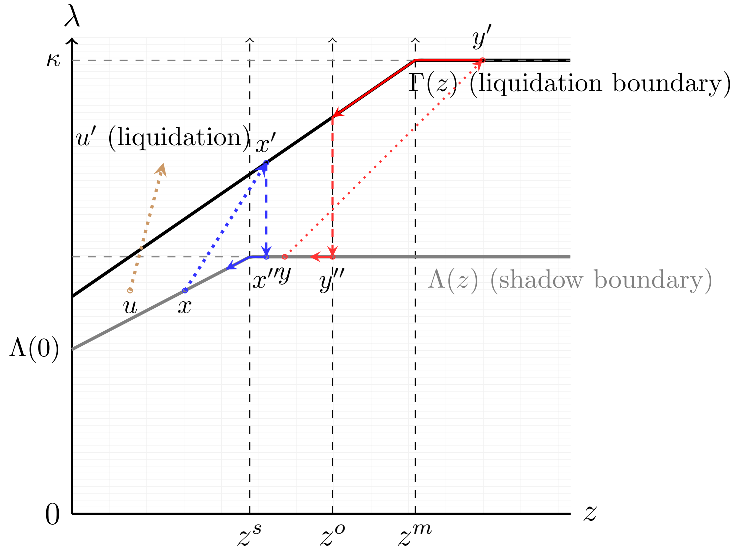
Corollary 2 *[Optimal Leverage] The optimal bank leverage, $\lambda^*(z)$, has the following bang-bang property:*

$$\lambda^*(z) = \begin{cases} \Gamma(z) & \textit{if } \Omega(z,\Gamma(z)) > \Omega(z,\Lambda(z)) \\ \\ \Lambda(z) & \textit{if } \Omega(z,\Gamma(z)) \leq \Omega(z,\Lambda(z)). \end{cases} \tag{15}$$

As with immediate accounting, under delayed accounting, leverage λ^* is a bang-bang control. It is at either the shadow or the liquidation boundary. The difference is that the solution depends on z. The intuition is the same. Banks risk liquidation when the returns Ω sufficiently counterbalance their liquidation risks. Since liquidation values are independent of leverage, banks risk liquidation when $\Omega(z,\Gamma(z)) > \Omega(z,\Lambda(z))$. As is common with bang-bang controls, leverage features discontinuities at points z^o such that $\Omega(z^o,\Gamma(z^o)) = \Omega(z^o,\Lambda(z^o))$.[29]

[29] In general, there could be multiple such points, although in the estimated model, we find only one such discontinuity.

Figure 6: Typical Trajectories of z and λ under Delayed Accounting



Notes: These panels depict the shadow and liquidation boundaries and the typical trajectories under delayed accounting characterized in Proposition 2.

We use Figure 6 to explain the dynamics implied by Corollary 2. The points $\{x, x', x''\}$ and $\{y, y', y''\}$ are part of different trajectories in the $\{z, \lambda\}$-space. Consider a bank that receives a default shock starting at $z = z_0$. Before the shock, the bank sets leverage at the shadow boundary at the point $x = \{z_0, \lambda^o\}$. The loan default leads to a jump from x to $x' = \left\{z_0 + J^z(z_0), \lambda^o + J^\lambda(z_0)\right\}$, right at the liquidation boundary. The bank remains solvent. Because the zombie loan jumps to a value below the discontinuity point z^o, the bank wants to avoid liquidation risk going forward. The bank sells loans to return to the shadow boundary at x''. After the asset sale, the zombie loan and leverage ratios travel continuously along the shadow boundary as the books slowly recognize the loss.

If a loan default event occurs starting from $y = \{z_1, \lambda_1\}$, the dynamics change. From that point, z subsequently jumps from z_1 to $z_1 + J(z_1) > z^o$. The bank opts to stay at the liquidation boundary, risking closure. Provided that no further loan default events occur, $\{z, \lambda\}$ travels left along the liquidation boundary. Once z reaches z^o, the bank chooses to delever to return to the shadow boundary at y''.

Next, we turn to Section 5, where we demonstrate how an estimated version of the model can reproduce all four motivating facts. We can already anticipate why the model can explain the facts through Figure 6. Following a loan default event, banks either revert to the shadow boundary by asset liquidation or maintain higher leverage at the liquidation boundary. In either scenario, banks have to sell fewer assets than under immediate accounting, yielding a gradual deleveraging process as in the data. During that process, future book losses are predictable, and the dynamics of book and market leverage differ.

4 Estimation and Matching Facts

This section describes how we map the model to the data and shows how it fits the facts from Section 2. More details are in Appendix Section F.

4.1 Model Parametrization

The model here is the same as that in Section 3, except we allow dividends to be a choice of the banker. We maintain risk neutrality but introduce a preference for smooth dividends. With risk neutrality, the bank's leverage choice is dictated by the risk–return tradeoff. Dividend smoothing allows us to more closely match the IRFs. To keep dividend payments stable even after a loan default loss, the bank delevers more slowly. To allow for dividend smoothing while keeping a risk-neutral objective, we endow the bank with Duffie–Epstein preferences with zero risk aversion and an intertemporal elasticity of substitution (IES) of $1/\theta$.[30] Recall that we assume that shareholders value bank equity differently from banks, which captures differences in the fundamental value of bank equity and the market value of bank equity.

We set $\{r^L, r^D, \Xi\}$ externally—see Appendix F—and jointly estimate $\{\rho, \rho^I, \theta, \varepsilon, \alpha, \kappa, \sigma, v_0\}$ via the simulated method of moments (SMM). We list the parameter values in Table 1. In Appendix Table 8, we show that the model matches targeted and untargeted moments well.

Jointly Determined Parameters. To produce model moment counterparts for each parameter draw, we simulate a quarterly panel from which we calculate the cross-sectional average moments and construct IRFs using the specification for the net-worth shock from Section 2. Our estimation targets the cross-sectional averages of book leverage, book equity growth rate, the market-to-book equity ratio, and the IRFs of bank liabilities and market leverage.[31] We require the model to match the charge-off rate and bank failure rate exactly.[32] We choose the arrival rate of the loan default shock to match a 0.12% quarterly net loan

[30]We show in Appendix G that calibrating $\theta = 2$ instead of estimating it slightly worsens the fit of the model but does not qualitatively alter the predicted responses of the bank variables to loan default shocks.

[31]Formally, the model is overidentified because each IRF in the data contains effectively 21 moments, one for each β_h in Eq. (1). In practical terms, these moments are highly correlated, so the de facto degree of overidentification is lower. Each IRF is well approximated by two moments: the jump on impact and the persistence.

[32]In practical terms, we impose a very large weight on the moment conditions for loan charge-off rates and bank failure rates (associated with σ and v_o), such that the estimation is forced to pick parameters to hit those moments exactly.

Table 1: PARAMETRIZATION

Parameter	Description	Target
	Externally set parameters	
$r^L = 1.01\%$	Loan yield	BHC data: avg. interest income/loans
$r^D = 0.51\%$	Bank debt yield	BHC data: avg. interest expense/debt
$\Xi = 12.5$	Regulatory maximum asset to equity ratio	Capital requirement of 8%
	Jointly determined – estimated	
$\rho = 2.24\%$	Banker's discount rate	Book equity growth rate: 2%
$\rho^I = 3.47\%$	Investor's discount rate	Market-to-book ratio of equity: 1.316
$\theta = 7.94$	Banker's inverse IES	Market leverage IRF
$\varepsilon = 1.12\%$	Loan loss rate in event of default	Mean book leverage
$\alpha = 4.16\%$	Speed of loan loss recognition	Liabilities IRF
$\kappa = 51$	Market-based leverage constraint	Liabilities IRF
$\sigma = 0.115$	Arrival rate of loan default shocks	Mean quarterly net charge-off rate of 0.12%
$v_o = 0.046$	Bank liquidation value	Quarterly bank failure rate of 3.65 basis points

Notes: This table summarizes the parameter values, their role in the model, and the data target used to set or estimate their value. The text provides more details.

charge-off rate, setting $\sigma = 0.115$. We choose v_o, the banks' liquidation value, to match a quarterly bank failure rate of 3.65 basis points based on FDIC data.[33]

Identification and Estimated Values. The growth rate of book equity is informative about bankers' discount rate ρ because this parameter governs the dividend payout rate. In the data, the growth rate of book equity equals 2.00%; we estimate ρ to be 2.24%. To estimate investors' discount rate ρ^I, we target the average market-to-book ratio.[34] From Section 3.1, the market-to-book ratio of banks is $Q = s/(1+z)$. We use the market-to-book ratio as a target since ρ^I enters the market valuation of banks s. We target an average market-to-book ratio of 1.316, which yields a value of $\rho^I = 3.47\%$.[35]

We use the IRF of market leverage as a target for θ.[36] Since dividends affect the market

[33]See the FDIC website here.

[34]Note that $\rho \neq \rho^I$ implies that bankers' and investors' valuation of bank equity differs, capturing reduced-form agency frictions. To keep the paper concise, we have opted not to focus on the incentive issues with delayed accounting. Corbae and Levine (2018) are the first to provide a quantitative assessment of regulatory policies modulated by agency frictions.

[35]Note that even though the estimated value of ρ^I is higher than ρ, our model is still consistent with agency models such as the model in Acharya and Thakor (2016), where the agent (banker) has a higher effective discount rate than the principal (investor). This is because the banker's objective includes curvature, increasing the effective discount rate of the banker above ρ^I. A useful benchmark is to consider the value of s under immediate accounting and $\theta = 1$. In that case, $Q = s = \frac{\rho}{\rho^I - \Omega^W}$. Thus, the estimated value of ρ^I is influenced by the dividend rate and the growth rate of equity as well as the data target for Q. For the target value of Q and the growth rate of equity induced by the joint estimation, it is easy to verify that $\rho^I > \rho$. Given our estimation, banker's effective discount rate is $\rho + \theta \cdot \Omega^W = 0.0224 + 7.94 \cdot 0.02 = 18.12\% >> 3.47\% = \rho^I$.

[36]Since we also target the IRF for liabilities and log market leverage is defined as the difference between

value of the bank, the IRF of market leverage to a net-worth shock is informative about θ. We estimate $\theta = 7.94$, which suggests a strong preference for near-constant dividend rates.

The distance between the shadow and the liquidation boundaries is determined by the loss size ε. Thus, given Ξ, the average book leverage ratio is informative about ε. We estimate $\varepsilon = 1.12\%$ to target an average book leverage ratio of 11.36.

We target the IRF of liabilities to identify κ and α. The loan loss recognition rate, α, governs how fast book equity reverts to fundamental equity. Recall that in response to a net-worth shock, book leverage jumps and reverts with the reversion rate in z. Hence, the mean reversion in the IRF for book leverage is informative about α, which we estimate to be 4.16%. The interpretation is that approximately 65% of unrecognized losses are recognized within 10 quarters. It is reassuring that the delay estimated from the cross-section is consistent with the data time series since net charge-offs taper off by the end of 2010, approximately two-and-a-half years after the trough in market values.

Finally, the value of κ determines the number of banks for which market-based liquidation is a concern. Banks located in the flat region of the shadow boundary (those with a high z) exhibit an immediate response in their liabilities to a loan default shock. Therefore, the initial jump in the IRF of liabilities provides insight on the proportion of banks on the flat region of the shadow boundary and, by extension, on κ. Appendix F shows that the model fits the data well.

4.2 Matching Facts

We evaluate the model's ability to reproduce the four facts from Section 2, focusing on the period between 2007 Q3 and 2019 Q4, during which banks experienced a large credit shock followed by a slow recovery.

Aggregate Shocks. We add aggregate shocks to our model to match the time series of Facts 1 and 3.[37] To back out a shock time series that mimics the GFC, we subject the values of three parameters, σ, α, and v_o, to an MIT shock, starting the model from the stationary distribution. That is, we choose the shocked values of these parameters such that the model approximately matches the aggregate net charge-off rates of bank loans—Panel (a) of Figure 7—and the cumulative bank failure rate by 2019 Q4 of 7.52%.[38] Banks learn in 2007 Q3 that the values of σ, α and v_o will be different for 10 (σ) and 50 (α and v_o) quarters, respectively, including 2007 Q3. Afterward, all three parameter values revert back to their baseline values

log liabilities and log market equity, this is equivalent to targeting the IRF of market equity.

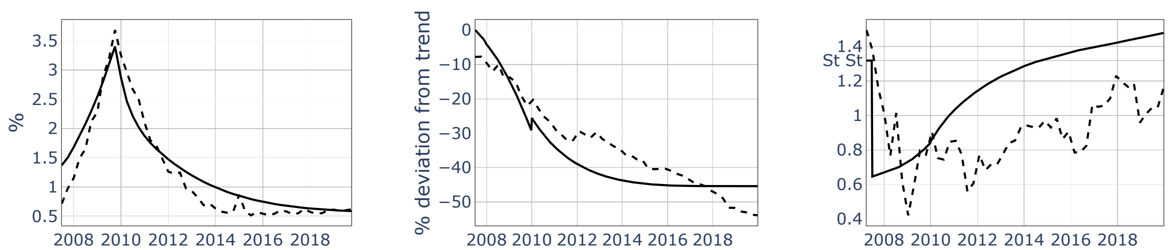
[37] Note that with idiosyncratic shocks and a continuum of banks, the law of large numbers guarantees that the aggregate time series generated by the model are deterministic.

[38] Based on FDIC data, 548 banks failed between 2007 and 2019, almost all of them before 2012, and there were 7288 banks in 2007. Thus, we target a cumulative bank failure rate of 548/7288=7.52%.

in Table 1. Specifically, we first assume that the arrival rate of loan default shocks σ jumps from the estimated value of 0.115 to $\sigma^{GFC} = 0.805$ between 2007 Q3 and 2009 Q4. After 2009 Q4, the arrival rate jumps back to $\sigma = 0.115$. Second, we assume that the speed of loss recognition jumps from the estimated value of $\alpha = 4.16\%$ to $\alpha^{GFC} = 9.78\%$ in 2007 Q3 and remains at this level until 2019 Q4, after which it reverts to α.[39] This captures the increased regulatory scrutiny of banks during and after the GFC, which forced banks to recognize losses more quickly. Finally, we also change the value of bankers' outside option, the liquidation value, from its calibrated value of $v_o = 0.046$ to its value over the period 2007 Q3 to 2019 Q4, $v_o^{GFC} = 0.01$.[40] Panel (a) of Figure 7 shows that these parameter

Figure 7: Crisis and Recovery in Model and Data

(a) Net Charge-off Rate (b) Loan Book Values (c) Fact 1: Tobin's Q



Notes: This figure compares the aggregate series of model-generated data (solid line) to the empirical data (dashed line). These series are based on a simulation that feeds in shocks chosen to match the times series of aggregate loan loss provisions (Panel (a)). Panel (b) presents the evolution of book loans as a deviation from a trend based on the 10 years before 2006 Q4. Panel (c) presents Tobin's Q. We plot the steady-state value of Tobin's Q for 2007 Q2—before the aggregate shock is realized—as a reference. The labels on the x-axis refer to the first quarter of the year.

assumptions generate a good fit of the aggregate net charge-off rate series. We also closely hit the cumulative bank failure rate at 7.58% relative to 7.52% in the data. In addition, the model reproduces the untargeted decline in the book value of loans, as Panel (b) of Figure 7 shows.[41] Our GFC shock causes aggregate loan book values to shrink by approximately 50% relative to trend, which is similar to the change in the data.

We use these values to show how the model fits Facts 1 and 3 from Section 2.

Fact 1. Market and Book Equity Value Divergence. Fact 1 is that the aggregate market value of bank equity differs from aggregate book equity, with particularly divergent dynamics during crises. By shocking the loan default arrival rate σ, Panel (c) of Figure 7 plots the time series of Tobin's Q, the ratio of market equity to book equity, in the data

[39]The increased value of α until 2019 Q4 allows the model to capture the decline in the net charge-off rates post-2010.

[40]The reason we need a lower v_o is that a higher loan default arrival rate and higher loan loss recognition rate would result in too many bank failures. Lowering v_o reduces the attractiveness of bankruptcy.

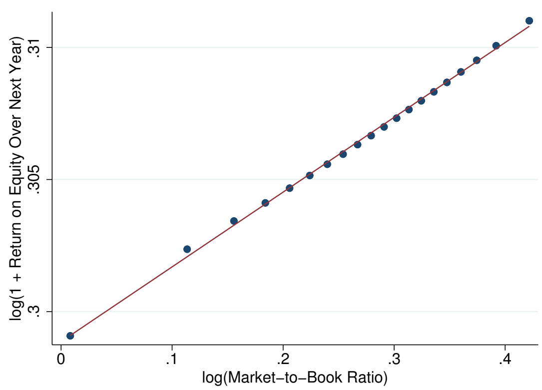
[41]Because book loans are growing, we detrend book loans in the model using the steady-state growth rate and in the data using the exponential trend of the 10 years prior to 2007 Q3.

(dashed line) and compares it to that in the model (solid line). The delayed loan loss recognition mechanism generates a sustained and pronounced decline in Tobin's Q of more than 50% on impact. This is driven entirely by little q, the ratio of fundamental equity to accounting equity, as we do not assume changes in investors' valuation of banks. In the data, Tobin's Q falls more gradually by more than 70%, bottoming out at the end of 2008. In the model, banks learn the path of aggregate shocks in the third quarter of 2007. As a result, the response of Q is concentrated at the very beginning.

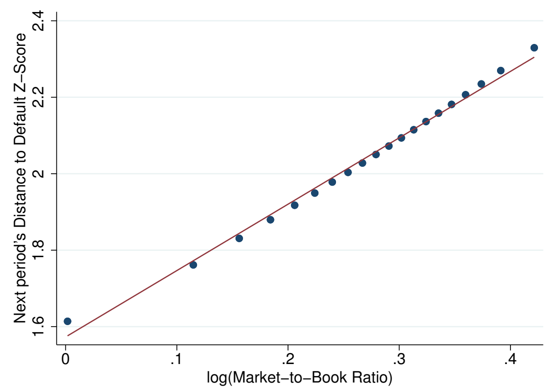
Fact 2. Predictive Power of Tobin's Q. The second stylized fact is that banks' Tobin's Q predicts their book ROE and the D2D measure, indicating that market values contain information about future cash flows that books do not. The model captures this predictability because market values contain information on unrecognized losses embedded in fundamental values. In Panels (a) and (b) in Figure 8, we show that the model generates the same upward-sloping relation between Tobin's Q and future ROE and D2D observed in the data.

Figure 8: Fact 2: Predictability

(a) Return on Equity



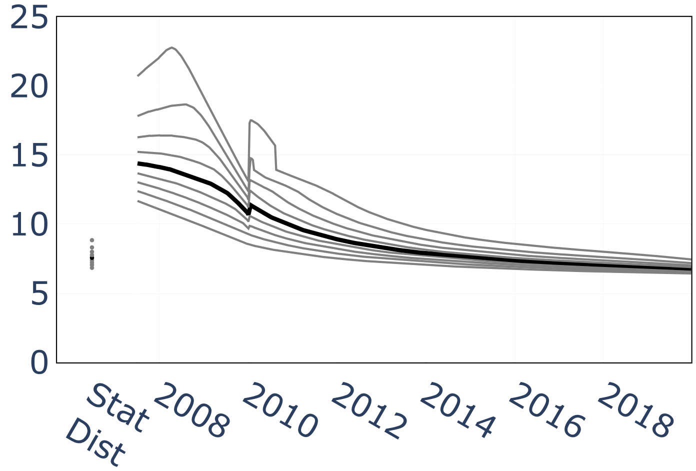
(b) Distance to Default



Notes: Panel (a) presents a cross-sectional binscatter plot of next-year's ROE over log Tobin's Q (log market-to-book ratio of equity). Panel (b) presents a cross-sectional binscatter plot of the distance to default over log Tobin's Q (log market-to-book ratio of equity). Both figures control for the book value of equity and equity capitalization. The data are from model-simulated data using the stationary distribution and the parametrization in Table 1.

Fact 3. Constraints. The third stylized fact is that banks avoid hitting the regulatory constraint and the market constraint by keeping a book equity buffer over the regulatory limit and a substantial buffer vis-à-vis the market leverage constraint, which allows an increase in the cross-sectional dispersion in market leverage during crises. We purposefully designed the model to capture the capital buffer over the regulatory minimum—recall Figure 6. Feeding in the MIT shocks to the three parameters as discussed above, Panel (c) of Figure 9 shows that we can also capture the increase in the cross-sectional dispersion of market leverage during the GFC, though not its full extent. Note that once the default arrival rate σ returns

Figure 9: Fact 3: Market Leverage Dispersion



Notes: This figure shows the distribution of market leverage for model-simulated data in response to the same sequence of default shock as in Figure 7. The bold line is the median, and the thin lines are cross-sectional deciles of market leverage. The stationary distribution of market leverage is plotted for reference. The year labels on the x-axis refer to the first quarter of the year.

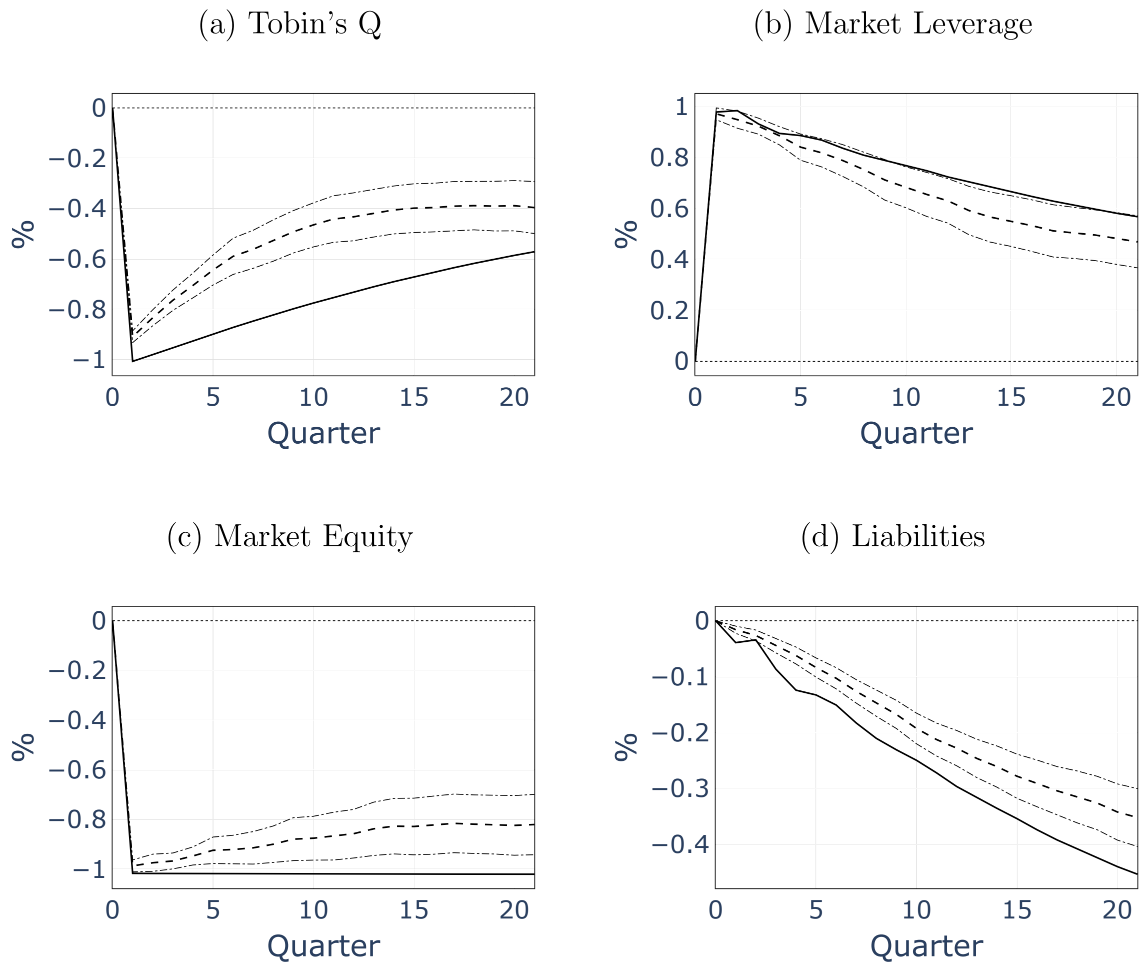
to its estimated value of 0.115, banks take on more risk by levering up. Our model abstracts from many features in the data that would induce more cross-sectional dispersion in market leverage, such as ex ante heterogeneity, fat-tailed default shocks, and time-varying investor risk premia. Nevertheless, our model captures approximately one-third of the increase in the leverage dispersion and the prolonged effects of the GFC.

Fact 4. Slow Leverage and Tobin's Q Dynamics. Figure 10 compares the IRFs of the data (dashed lines) with those generated by the model (solid lines).[42] We show the IRFs of Tobin's Q in Panel (a), market leverage in Panel (b), market equity in Panel (c), and total liabilities in Panel (d). All plots also include the 95% confidence bands on the data IRFs. Our model reproduces the slow return to pre-shock levels in Tobin's Q via the dynamics of little q, whereby the defaults are only slowly recognized in accounting values relative to fundamental values—see Panel (a). We can also generate an IRF of market leverage that is within the confidence bounds of the data—see Panel (b). Panel (c) shows that the model reproduces the slow recapitalization process following a negative shock: market equity does not recover at all in the model, while it recovers by only 20% in the data after five years. Finally, Panel (d) shows that our model captures the slow decline in banks' liabilities in the

[42] To compute the model IRFs, we first solve and simulate the model using the baseline parameter values from Table 1 and construct bank market returns as explained in Section G.2 Eq. (70). We run pooled ordinary least squares (OLS) regressions of the demeaned variable of interest on banks' market return and 20 lags using the simulated data. Finally, we take the coefficients, multiply each by -1%, and compute the IRF at horizon h as the sum of the coefficients up to lag h.

data.

Figure 10: Fact 4: Model vs. Data Impulse Responses



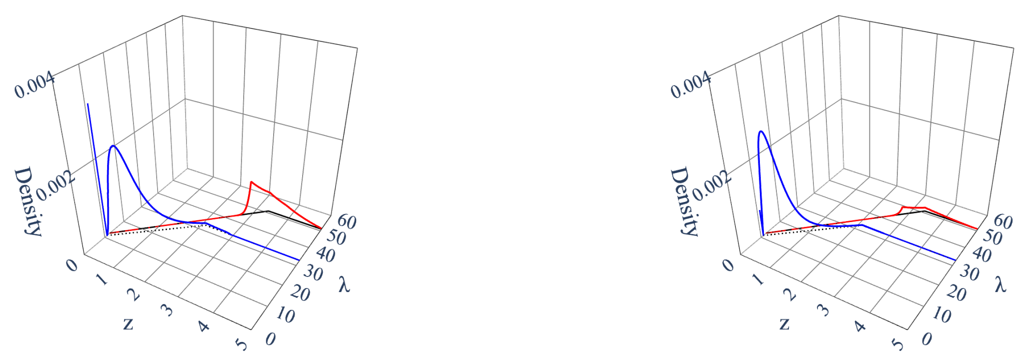
Notes: The figures present the impulse response functions of model-simulated data (solid line) for the benchmark calibration and compares them to those from the data (the dashed line represents the point estimates and the dash-dot lines the 95% confidence interval). We show the impulse response function of Tobin's Q in Panel (a), market leverage in Panel (b), market equity in Panel (c), and liabilities in Panel (d). To compute the model IRFs, we first solve and simulate the model using the baseline parameter values from Table 1 and construct bank market returns as explained in Section G.2 Eq. (70). We run pooled OLS regressions of the demeaned variable of interest on banks' market return and 20 lags using the simulated data. Finally, we take the coefficients, multiply each by -1%, and compute the IRF at horizon h as the sum of the coefficients up to lag h.

4.3 Effects of Accounting Rules

The move to the CECL accounting standard—in effect for all financial institutions since 2023 and for most publicly traded banks since 2020, with optional implementation because of the COVID-19 shock—marked a significant shift in how banks and financial institutions account for credit losses. CECL requires banks to estimate and record expected credit losses over the life of a loan at the time of origination or acquisition. This forward-looking approach contrasts sharply with the previous incurred loss model, which recognized losses only after they became probable. As a result, CECL encourages earlier recognition of credit losses and promotes greater transparency in financial reporting. In this section, we show that an accounting reform in the spirit of CECL, i.e., one that accelerates the speed of loan loss recognition, features a tradeoff.

Figure 11: Comparison of Stationary Distributions for Different α

(a) Baseline Parameters: $\alpha = 4.16\%$ (b) Faster Recognition: $\alpha = 6\%$

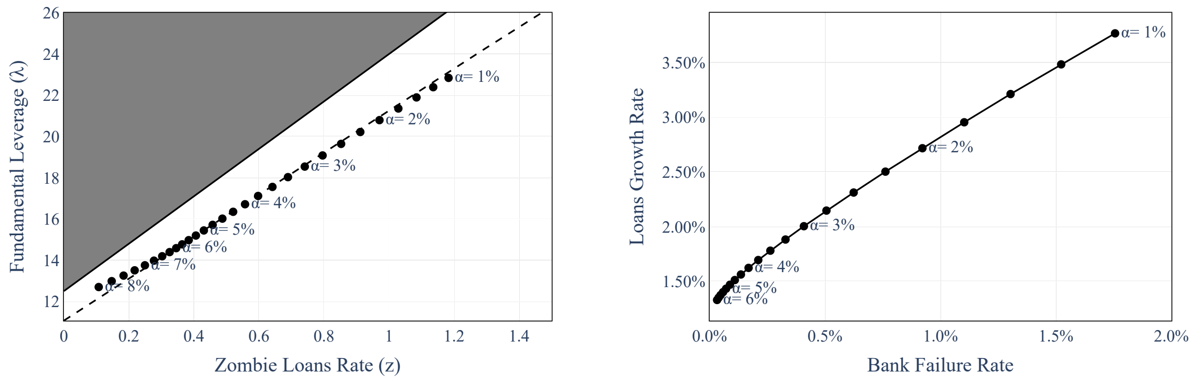


Notes: This figure presents a two-dimensional plot of the stationary distribution of banks across (λ, z). The black dashed line traces out the shadow boundary $\Lambda(z)$ and the solid black line the liquidation boundary $\Gamma(z)$. The blue and red lines are the density of banks conditional on their choosing the shadow and liquidation boundaries, respectively. For visualization purposes, the density conditional on banks' choosing the liquidation boundary has been multiplied by 20, as it is otherwise not visible. Panel (a) sets parameters at their benchmark levels in Table 1, and Panel (b) increases α to 6%.

We capture an accounting rule policy change through changes in α. A relaxation of accounting standards increases loan growth in our model while also increasing bank liquidation risk—and vice versa for a tightening of accounting rules in the spirit of CECL. To understand why this is the case, recall that the zombie loan ratio z drifts toward zero at rate $\mu^z = -z\left(\alpha + \mu^W\right)$ and that equity growth μ^W depends on the levered return. In turn, the jump in z increases with leverage. Thus, for any initial value of z_0, the expected value of z_t should lower with α, conditional on the bank's surviving. However, higher values of z lead to more frequent liquidations, shifting the mass of banks toward $z = 0$, as failed banks are replaced with new banks initialized at $z = 0$. To visualize these distributional changes, Figure 11 plots the density of $\{z, \lambda\}$ for two values of α. The density is plotted on the z-axis, whereas the y- and x-axes represent the leverage and zombie loan ratios, respectively. The shadow boundary (in blue) and liquidation boundary (in red) are projected onto the x–y plane in Figure 6. The invariant distribution of banks resides on the liquidation and shadow boundaries. When we compare Panel (a) with Panel (b), an increase in the loss recognition rate α translates into a greater mass of banks with lower fundamental leverage and, consequently, lower equity and loan growth. On the flip side, lower values of z also decrease liquidations, as fewer banks are on the liquidation boundary. This is the source of the tradeoff between loan growth and bank liquidation risk that we discuss next.

Figure 12: Comparison of Steady States for Different αs: Effect of Delayed Loss Recognition on λ and z

(a) Leverage vs. Zombie Loan Ratios (b) Liquidations vs. Loan Growth



Notes: Panel (a) presents cross-sectional averages of λ and z from the stationary distribution for different values of α. The gray shaded area presents the liquidation set and the dashed line the shadow boundary. Panel (b) presents the cross-sectional average of banks' loan growth rate and the average bank failure rate for different levels of α. We assume that all other parameters remain at their benchmark levels shown in Table 1.

To illustrate this tradeoff, Panel (a) of Figure 12 presents the steady-state cross-sectional averages of the zombie ratio z and fundamental leverage λ obtained from the stationary distribution of banks for two values of α. There is a clear negative relation between α and the average levels of z and λ. Strikingly, although the fundamental leverage ratio λ differs for different α, the average book leverage is essentially identical in each case: book leverage ranges from 11.05 with $\alpha = 1\%$ to 11.59 with $\alpha = 8\%$. This occurs because most banks remain at the shadow boundary of the regulatory constraint. Hence, all of these economies look similar in terms of accounting values, while the fundamental leverage and liquidation risk differ significantly.

Panel (b) of Figure 12 shows how changes in α induce a policy trade-off between liquidation risk and loan growth. The graph shows that there is a range of values $\alpha \leq 6\%$ for which faster loan loss recognition induces a decline in growth of lending and bank failures. A policy tradeoff is present since banks do not internalize the social costs of liquidation when taking risk. Having clarified this tradeoff, we move to the normative implications of our model.

5 Policy Implications

In this section, we investigate the normative implications of changes in accounting standards. We introduce an appropriate welfare notion to the theoretical model and then use our estimation to derive normative implications quantitatively.

5.1 Normative Analysis

We embed our bank Q-theory into general equilibrium, resulting in a microfounded social welfare function.

Nonfinancial Agents. We provide a full description of the nonfinancial sector and the derivations of the social welfare function in Appendix C. Here, we summarize the environment. A representative risk-neutral household holds wealth in bank stocks and capital in a production sector. In the spirit of He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014), banks specialize in loans, an essential source of funding for a most productive sector that households cannot directly fund. Households can fund a less productive sector.

Capital in the loan-funded sector is randomly destroyed, leading to the loan defaults encountered earlier. When bank equity is scarce, which we assume, the return to capital for the less and most productive sectors generates perfectly elastic deposit supply and loan demand curves, like those in Section 3.

The key assumption motivating regulation is that banks do not internalize the social costs of liquidations. When a bank is liquidated, loan losses, which are only ε if the bank survives, increase to $\varepsilon + (1-\psi)(1-\varepsilon)$ if the bank is liquidated—$\psi < 1$ captures bank restructuring costs.[43] We assume the social cost of liquidation is large enough that liquidations are never socially desirable:

Assumption 2 *Liquidations are socially inefficient:* $r^L - r^D \leq \sigma(\varepsilon + (1-\psi)(1-\varepsilon))$.

Social Welfare. A social welfare function aimed at maximizing the representative household's welfare can be simplified to maximizing the present value of aggregate bank dividends:

$$\mathcal{P}[\alpha, \Xi, \{g_0\}] \equiv \int_0^\infty \int_0^\infty \mathbb{E}\left[\int_0^\infty \exp(-\rho t)\, cW_t dt | W_0 = W, z_0 = z\right] g_0(z, W)\, dz dW, \quad (16)$$

where $g_0(z, W)$ is the initial joint distribution of z and W. The expectation considers the formation of new banks after banks are liquidated. In contrast to the bank's private objective, the planner internalizes the social costs.

Immediate Accounting – Normative Analysis. To develop intuition, we solve for the optimal capital requirement under immediate accounting, distinguishing between the socially optimal leverage and the optimal capital requirement. It turns out that under immediate

[43] Namely, when a bank is liquidated, the social losses are not only ε but also the additional loss $(1-\psi)$ on the remainder of the bank's loans. Bankruptcy spillovers are discussed in Bernstein, Colonnelli, Giroud and Iverson (2019).

accounting, the objective in 16 can be written as a static risk–return tradeoff that dictates the social return on leverage. Because of scale independence, the solution pins down the same optimal leverage across banks. We distinguish between first-best leverage, i.e., that chosen by the planner, and the second-best regulation, which does not directly control leverage but anticipates the banks' best response to the regulation.

Proposition 3 *[Optimal Regulation] The first- and second-best regulations are given by the solution to the following optimization problems:*

1. **First Best: Socially Optimal Leverage.** *Let the optimal (first-best) leverage λ^{fb} be the socially optimal leverage λ considering only market-based liquidations. The first-best leverage solves:*

$$\Pi^{fb} = \max_{\lambda} \underbrace{\left(r^L - r^D - \sigma\left[\varepsilon + (1-\psi)(1-\varepsilon)\mathbb{I}_{[\lambda>\Lambda]}\right]\right)}_{\text{social return of leverage}} \lambda. \tag{17}$$

The optimal leverage is $\lambda^{fb} = \kappa\left(1+\varepsilon(\kappa-1)\right)^{-1}$.

2. **Optimal Capital Requirements.** *Let the optimal (second-best) capital requirement Ξ^* be the socially optimal value of Ξ, taking as given the bank's optimal response (13) and considering both regulatory and market-based liquidations. The optimal capital requirement solves:*

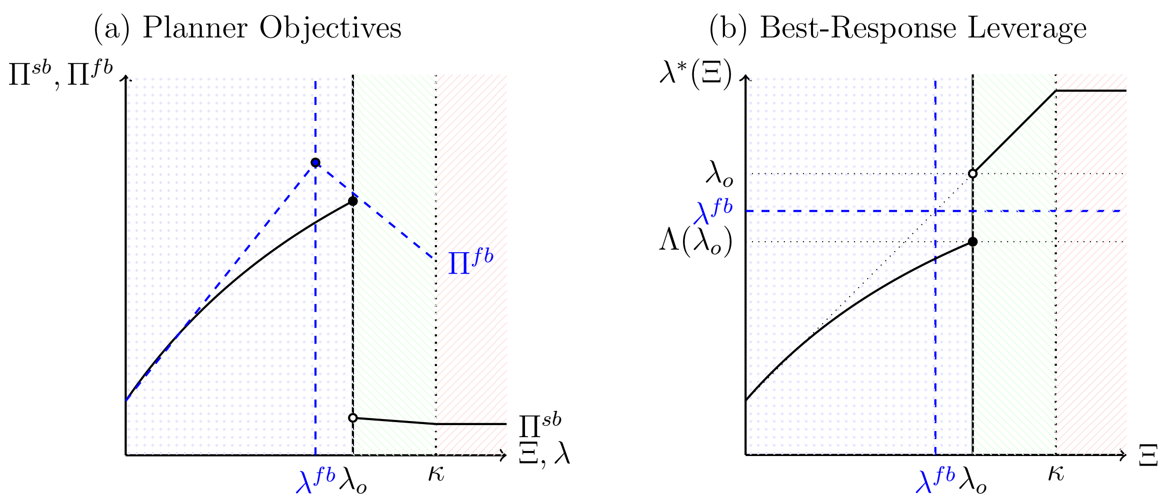
$$\Pi^{sb} = \max_{\Xi} \underbrace{\left(r^L - r^D - \sigma\left[\varepsilon + (1-\psi)(1-\varepsilon)\mathbb{I}_{[\lambda>\Lambda]}\right]\right)}_{\text{social return of leverage}} \lambda^*(\Xi). \tag{18}$$

2.a. First Best: Laissez-Faire Regulation. *If under laissez faire banks do not risk liquidation, $\kappa \le \lambda^o$, laissez faire achieves the first best.*

2.b. Second Best: Capital Requirements. *If under laissez faire banks risk liquidation, $\kappa > \lambda^o$, the first-best solution is unattainable, and $\Pi^{sb} < \Pi^{fb}$. The optimal capital requirement is $\Xi^* = \lambda^o$, and banks set leverage at the shadow boundary, $\lambda^{sb} = \lambda^o\left(1+\varepsilon(\lambda^o-1)\right)^{-1}$. Thus, if regulation is warranted, leverage is lower than the first best, $\lambda^{sb} < \lambda^{fb}$.*

The proposition clarifies the role of capital requirements. Under immediate accounting, the socially optimal leverage is given by a static risk–return tradeoff, encoded in the social return of leverage. Because it is socially desirable to avoid liquidations, the planner sets first-best leverage at the shadow boundary of the market-based constraint: the value that maximizes loan growth while avoiding liquidations. Recall from Section 3.2 that λ^o is the level of leverage at which banks switch from no risk-taking to risk-taking. When the market-based constraint is sufficiently tight, $\kappa \le \lambda^o$, banks set leverage at the shadow boundary, so laissez faire achieves the first best. When banks risk liquidations absent regulation—i.e., when $\kappa > \lambda^o$—capital requirements are warranted but cannot implement the first best.

Figure 13: First-Best Leverage and Optimal Regulation (Immediate Accounting)



Notes: These panels show the regulator's problem under immediate accounting, in terms of the planner's objectives (left panel) and the bank's behavior λ^* in response to regulation (right panel) for the case where $\kappa > \lambda^o$. The planner's objective under the first best is denoted by Π^{fb} and under the second best by Π^{sb}. The right panel shows the bank's best response.

Capital requirements cannot achieve the first best because they come at a cost. Figure 13 provides intuition for why this is so. The dashed curve of Panel (a) in Figure (13) plots the objective in Π^{fb} in terms of λ—it is increasing up to the shadow boundary of κ. The solid curve of Panel (a) plots Π^{sb} as a function of Ξ. Panel (b) plots the banks' best response $\lambda^*(\Xi)$. Banks set leverage at the shadow boundary $\Lambda(\Xi)$ if $\Xi \leq \lambda^o$ and at the liquidation boundary $\Lambda(\kappa)$ if $\Xi > \lambda^o$. Hence, any value of $\Xi > \lambda^o$ leads to liquidations after the first default, an outcome that is socially inefficient. To discourage banks from risking liquidations, the regulator must set $\Xi = \lambda^o < \kappa$. However, when the capital requirement is set to $\Xi = \lambda^o$, banks keep a capital buffer setting their leverage to the shadow boundary of Ξ. This is below the first best, which would be the shadow boundary of κ. This regulatory capital buffer is why a range of leverage values $(\Lambda, \lambda^o]$ cannot be implemented through capital requirements. This range of values includes the first best.

Capital requirements are second-best instruments because their enforcement requires banks to be liquidated whenever they violate the regulatory limit. This punishment induces banks to keep a capital buffer beyond the necessary amount to avoid market-based liquidations. Thus, the cost of capital requirements is inefficiently low provision of credit in comparison to the first best. Despite this cost, capital requirements are nonetheless preferable to laissez faire. Next, we show that, beyond providing a good description of the dynamics of Tobin's Q and leverage, delayed accounting provides a valuable additional tool to regulators.

Adjustment Speed and Optimal α. Because capital requirements are imperfect instruments, regulation may improve upon the second-best outcome under immediate accounting by exploiting α as a policy tool. Recall from Section 4.3 that α induces a tradeoff between loan growth and bank liquidation rates. As α approaches infinity, leverage will be set at the shadow boundary of Ξ, and there will be no liquidations. Under finite values of α, the capital buffer that inefficiently limits lending is relaxed, but bank liquidation risk is increased.

Solving analytically for the socially optimal $\{\alpha, \Xi\}$-mix requires solving for the intractable joint dynamics $\{z, W\}$. However, the social welfare function has a convenient HJB representation.

Proposition 4 *[Optimal Regulation] Let g_0 be the initial joint distribution of $\{z, W\}$. The regulation with delayed accounting maximizes*

$$\mathcal{P}^*\left[\{g_0\}\right] \equiv \max_{\{\alpha,\Xi\}} \mathcal{P}\left[\alpha, \Xi, \{g_0\}\right] = \max_{\{\alpha,\Xi\}} \int_0^\infty W \int_0^\infty p\left(z\right) g_0\left(z, W\right) dz dW, \tag{19}$$

where $p(z)$ is the social value of a bank, which satisfies:

$$\rho p\left(z\right) = c + p_z\left(z\right)\mu^z + p\left(z\right)\mu^W + \sigma J^p\left(z\right), \quad \textit{and}$$

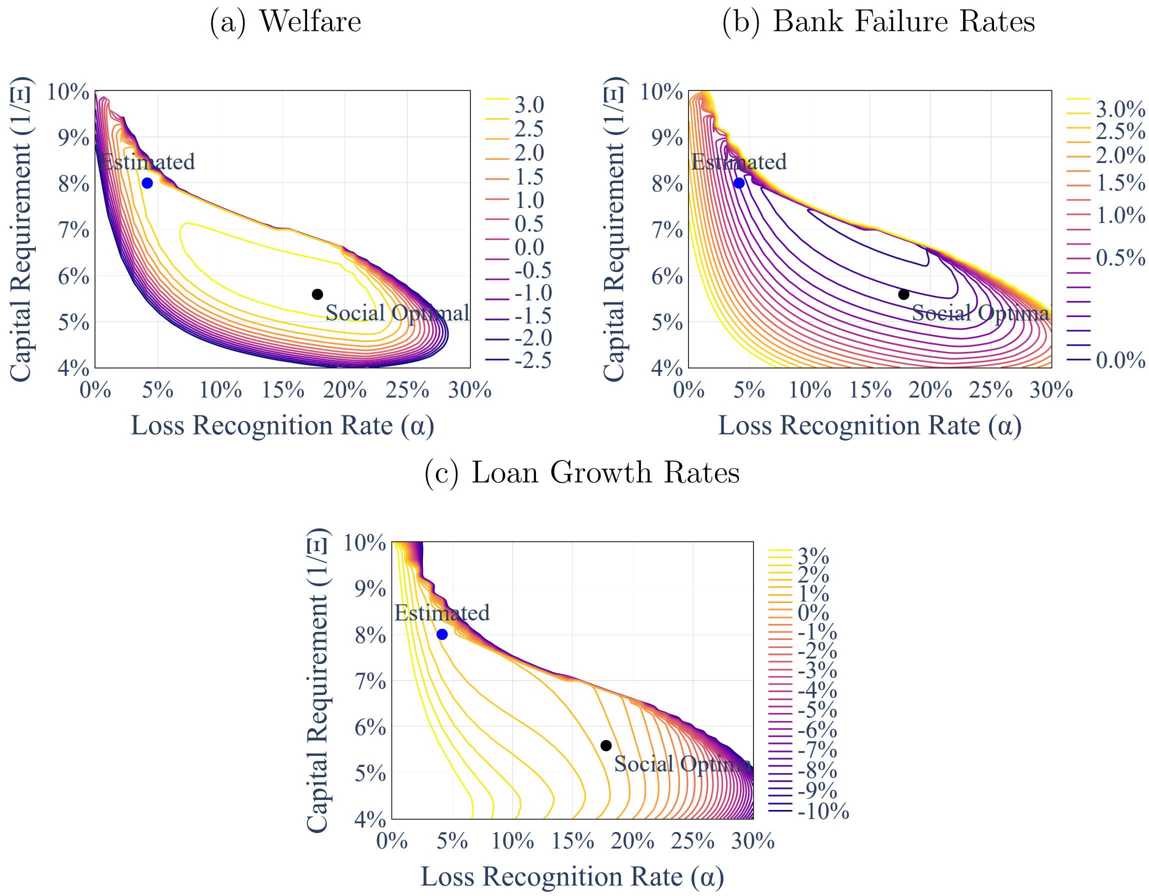
$$J^p\left(z\right) = \left[p\left(z + J^z\right)\left(1 - \varepsilon\lambda\right)\mathbb{I}_{[\lambda \leq \Lambda(z)]} + p\left(0\right)\left(1 - \left(\varepsilon + \left(1 - \psi\right)\left(1 - \varepsilon\right)\right)\lambda\right)\mathbb{I}_{[\lambda > \Lambda(z)]} - p\left(z\right)\right].$$

The socially optimal $\{\alpha, \Xi\}$-mix is given by a g_0-weighted average of the social value of an individual bank, $p(z)$. The function $p(z)$ is the present value of bank payouts. Notice that the social value is isomorphic to the private value, except that the planner internalizes the liquidation cost in the jump term. This representation allows us to obtain the optimal policy $\{\alpha, \Xi\}$-mix numerically.

5.2 Microprudential Implications: Optimal Regulation

In this subsection, we study the microprudential policy implications of our model and derive the optimal combination of $\{\alpha, \Xi\}$ numerically using our estimated model. This also allows normative assessment of speedier loss recognition rules, as implied by the recent move to the CECL accounting model. To this end, we consider the objective of maximizing social welfare after a one-time change in both α and Ξ, starting from the estimated stationary distribution and transitioning to a new stationary distribution after the policy change. We discuss the results in terms of Ξ^{-1}, which translate into capital requirements.

Figure 14: Optimal Microprudential Policy and Isovalues



Notes: Panel (a) shows the values of social welfare $\mathcal{P}[\alpha, \Xi, \{g_0\}]$ for each choice of Ξ and α. Panels (b) and (c) show the bank failure rates and the cross-sectional average of banks' loan growth rates, respectively, at the stationary distributions of the different (Ξ, α) combinations.

From Section 5.1, we learned that the optimal policy maximizes the weighted average social value of banks, which includes the social cost of bank failures. Of course, it is not trivial to estimate the social cost of bank failures empirically. However, we can obtain an estimate by assuming that the status quo regulation has optimally set Ξ, given our estimated accounting rules. The implied social cost of banking failure then justifies the existing capital requirements under the current accounting rules as the optimal requirement. We find that the social cost supporting the rationale for current regulations is equivalent to an annualized negative dividend rate of -2.65%, which we hold constant across new combinations of $\{\alpha, \Xi\}$.[44]

[44]The social cost of default is the jump term after a default event: $p(0)(1-(\varepsilon+(1-\psi)(1-\varepsilon))\lambda(z))\mathbb{I}_{[\lambda>\Lambda(z)]}$ from the definition of $J^p(z)$ in Eq. (19). In our numerical exercises, most banks choosing $\lambda > \Lambda(z)$ choose the market-based liquidation boundary, and hence, $\lambda(z) = \kappa$. Using our estimated values, we obtain a value for this term of -1.17. Bank liquidations average 0.05% per year. The annuity value of a social loss is $-1.17/\rho = -1.17/0.0224$. Multiplying the liquidation rate of 0.05% by the annuity value translates the cost into a flow cost of -2.65% per year.

Figure 14 summarizes the results. It presents contour plots for welfare in Panel (a), bank failures rates in Panel (b), and loan growth rates in Panel (c) as a function of α and Ξ. The two dots in each figure mark the estimated values and the socially optimal values. Recall from Figure 12 that, for a fixed Ξ, α governs a tradeoff between the frequency of bank liquidations and loan growth. At the optimal values of α and Ξ and relative to their estimated levels, lending growth rates are reduced by 46 basis points, while bank liquidation rates also decline by approximately 10 basis points. The optimal policy suggests that expediting loss recognition should be a regulatory priority: α is 17% at the optimum, compared to the baseline estimated value of 4.16%. To put these numbers in perspective, the reform would bring the half-life of zombie loans from four years to just a year and a half. However, the optimal policy couples this change with a looser capital requirement: the optimal capital requirement goes from the 8% mandated by Basel III standards down to approximately 5.5%, closer to the requirement under Basel II.

To understand what drives these welfare gains, we note that social welfare $\mathcal{P}[\alpha, \Xi]$ is well approximated by the following aggregate bank moment[45]:

$$\mathcal{P}[\alpha, \Xi] \approx \frac{\mathcal{C} - \mathcal{S}}{\rho - (\mathcal{G} - \mathcal{C})}.$$

In this approximation, $\mathcal{C}$ stands for the aggregate dividend rate, $\mathcal{S}$ for the flow of social losses, and $\mathcal{G}$ for the aggregate ROE before dividends. The flow of social losses $\mathcal{S}$, which acts as a negative dividend, is approximately the failure rate multiplied by the present value of the social cost of liquidations, e.g., $\mathcal{S} \approx 2.65\%$. In the data, the failure rate of banks is very small. Hence, to justify the current level of capital requirements, the social cost of default must be large. As a result, welfare is sensitive to the failure rates even though the rates are low. When α is fixed at its estimated value of $\alpha = 4.16\%$, regulation can limit the flow of social costs only with tighter capital requirements. When regulators are given the additional tool of speeding up loss recognition by choosing an optimally higher value of α, they shift the distribution of z toward lower values and away from the liquidation boundary—recall the distribution shifts in Figure 11. Thus, with fewer zombie loans, capital requirements can be even relaxed without increasing liquidations. In contrast, an increase in α reduces bank liquidations by two-thirds, bringing $\mathcal{S}$ down from 2.65% to 1.8%. While banks would appear more levered under the reform—book leverage would increase from 11.1 to 15.1—this change is only cosmetic, as fundamental leverage increases only slightly from 16.5 to 17.1. Relaxing the bank capital requirements increases banks' ROE, $\mathcal{G}$, by approximately 1%. An increase in bank profitability without an increase in liquidations is possible because the reform reduces banks' incentives for hidden risk-taking and therefore narrows the cross-sectional distribution

[45]For example, at the optimal regulation, the approximation differs from the numerical value by less than 1%.

of leverage. It results in safer banks with book values closer to fundamental values. Safe banks reduce their excessively large capital buffers, while risky banks are forced to delever faster. The welfare gains from the reform are only somewhat mitigated by an undesirable increase in dividends, $\mathcal{C}$, which offsets the increase in $\mathcal{G}$.[46]

In sum, moving accounting values closer to fundamental values makes the banking system safer. In addition, our exercise suggests that accounting standards and capital regulation should be jointly optimized: tighter accounting standards require looser book regulations to target the same fundamental leverage. The next section explores the macroprudential implications of our model.

5.3 Macroprudential Implications: CCyB

In this section, we analyze the effects of an aggregate shock under three different regulatory regimes: (i) one with a constant capital requirement and delayed accounting as estimated in Section 4, (ii) another with a CCyB in the presence of delayed accounting, and (iii) another with a countercyclical accounting rule.[47] Our findings indicate that delayed accounting can inadvertently influence the outcomes of a CCyB by potentially increasing the risk-taking behavior of banks, thereby challenging the widely held belief that CCyBs mitigate credit cycles.[48] By contrast, relaxing accounting rules during a loan default crisis would lead to fewer bank failures. This is because under a CCyB with delayed accounting, banks react with more risk-taking to the reduction in the capital requirement.

To consider a default crisis that mimics the patterns of the GFC, we introduce a time-varying loan-default arrival rate that is double the estimated value of $\sigma = 0.115$ at its peak:

$$\sigma_t = \sigma \left(1 + \exp(-\eta(t-\tau)^2)\right). \tag{20}$$

The scalar η governs the persistence of the shock—such that σ_t returns to σ after approximately 6 quarters—and τ governs when the aggregate shock peaks—such that σ_t peaks two quarters after $t = 0$.[49]

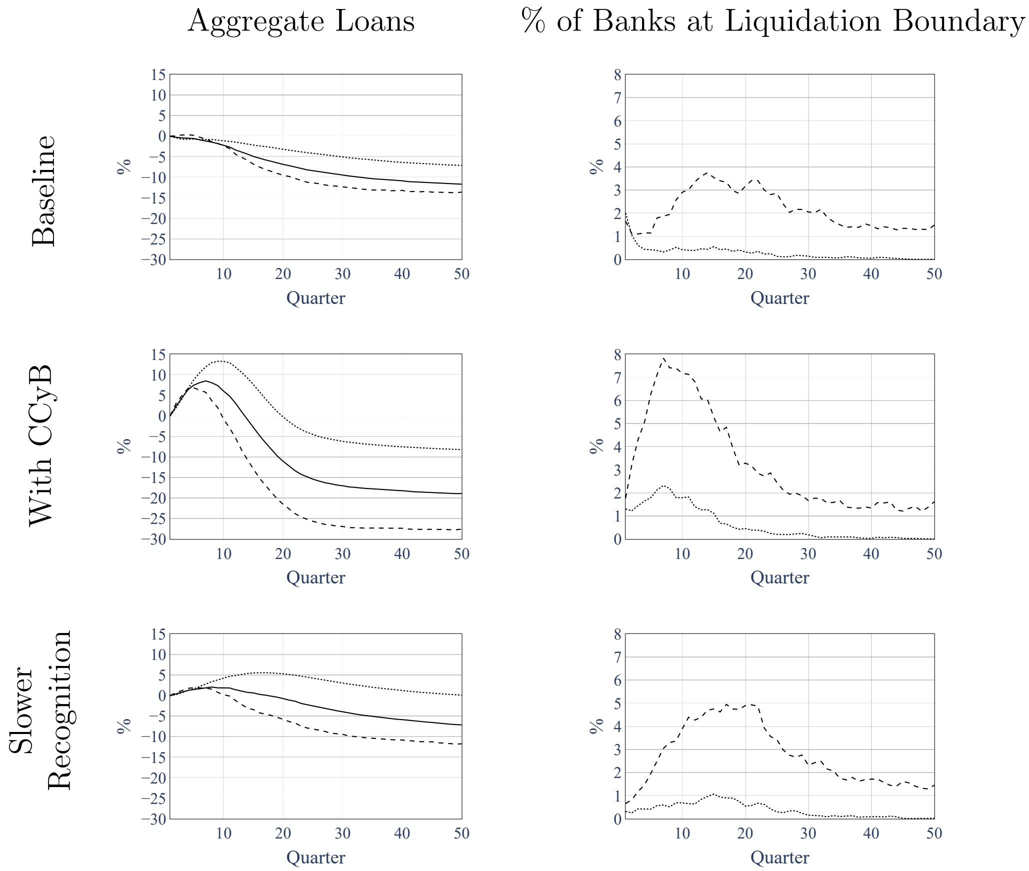
[46] Recall that as $\mathcal{G}$ increases, banks pay more dividends. This is because wealth effects dominate substitution effects for the estimated value of θ.

[47] For work on the economic effects of CCyB see Benes and Kumhof (2015), Gambacorta and Karmakar (2018), Faria-e Castro (2021), Simon (2021).

[48] According to the BIS, "Basel III requires that the CCyB be activated and increased by authorities when they judge aggregate credit growth to be excessive and to be associated with a build-up of system-wide risk. The buffer would subsequently be drawn down in a downturn to help ensure that banks maintain the flow of credit in the economy".

[49] We start the simulation at the stationary distribution. Banks learn about the path of σ_t at $t = 0$.

Figure 15: Macroprudential Policy Effects



Notes: The left column shows the percentage deviation from trend of aggregate loans following the aggregate shock to the arrival rate of loan defaults in Eq. (20) under the three policies studied. The right column shows the fraction of banks operating at the liquidation boundary for each quarter after the aggregate shock. In all exercises, we do not replace failed banks, motivated by the idea that there is little bank entry during a banking crisis. The top row presents the baseline case, where Ξ and α are constants at their calibrated and estimated values, respectively. The middle row presents the case under $CCyB$, where the capital requirement, Ξ_t^{CCyB}, follows Eq. (21). The bottom row is the case where the accounting rule α_t^{CAyB} is time-varying and relaxed after an adverse aggregate shock. Aggregate (fundamental) loans are depicted as solid lines, "low-shock" banks as dotted lines, and "high-shock" banks as dashed lines.

Figure 15 shows how aggregate lending (left column) and bank failure risk (right column) respond to an aggregate shock under the three policy regimes. The solid lines in the left column are the percentage deviation of aggregate loans from steady-state trend growth. The right column shows the fraction of banks that operate at the liquidation boundary. We distinguish "high-shock" banks, those hit by an above-average number of loan default events (dashed lines), and "low shock" banks, those hit by a below-average number of loan default events (dotted lines).[50]

The top row of the figure shows the results under our baseline policy regime of a constant capital requirement Ξ and our estimated loan-loss recognition rate α. The aggregate shock

[50]Recall that the default intensity σ_t operates i.i.d. across banks even though all banks' probability of being hit has increased.

leads to a slow decline in aggregate loans (left panel) because a larger mass of banks moves to the liquidation boundary (right panel), where failure is imminent. The equity capital of failed banks is wiped out, leading to subsequently lower credit supply.

In the middle row of Figure 15, we analyze a CCyB, modeled via a time-varying Ξ_t:

$$\Xi_t = \Xi \left(1 + \left(\frac{\Xi^{CCyB}}{\Xi} - 1\right) \exp(-\eta(t-\tau)^2)\right). \tag{21}$$

We choose the same values for η and τ as in Eq. (20), adding Ξ^{CCyB} such that the effective capital requirement falls from 8% to 6% at the peak of the crisis and increases back to 8% after the crisis ends. Ξ_t thus mirrors the path of σ_t.[51] Compared to the baseline scenario, the CCyB initially triggers a brief surge in lending but also more failures as the relaxation of the constraint incentivizes banks to increase leverage to boost returns. As the crisis progresses, aggregate lending falls relative to that in the baseline scenario, settling at a lower trend. This results from an increase in bank failures that deplete aggregate bank equity. Interestingly, the effect is not only driven by the high-shock banks. There are also more liquidations among the low-shock banks. Indeed, when the CCyB eases, a mass of banks who inherited a high zombie ratio z opts to risk liquidation by increasing leverage. All in all, the CCyB increases risk-taking behavior across the board, resulting in an initial increase in lending that is eventually offset by a greater number of failures. Contrary to the intended effects of the CCyB, the policy amplifies the credit cycle.

The bottom row of Figure 15 presents the results for a policy that slows down recognition of loan losses. We study a time-varying α, denoted as α_t^{CCyB}, that takes the same shape as Ξ_t in Eq. (21). In this case, we relax α from the estimated value of 4.16% to 2.16% at the peak of the crisis. The policy induces a much smoother lending series than the CCyB regime. While relaxing accounting rules during credit risk events also induces more risk-taking than in the benchmark, risk-taking is much lower than in the CCyB regime. The reason for this is that the countercyclical accounting rule primarily targets high-shock banks. Low-shock banks have fewer zombie loans on average, so the accounting relaxation does not strongly incentivize them to take on risk. Lending declines by less than in the benchmark because relaxing accounting standards postpones the deleveraging of high-shock banks. As a result, our findings suggest that relaxing loss recognition rules during times of heightened default risk can be a more targeted policy than the CCyB in this setting.

Although delayed accounting and the CCyB are similar in that they both relax the regulatory constraint in the event of a negative shock, they differ in a critical respect. The CCyB is not conditional on the bank's receiving negative shocks. This makes the policy untargeted and also changes the policy's timing: the CCyB may relax a bank's constraint *before* it is hit

[51] This is consistent with Basel III and current practice, where the CCyB varies between 0% and 2.5%.

with a shock, which encourages more risk-taking. In contrast, delayed accounting delivers regulatory relaxations only conditional on receiving a negative shock. This makes delayed accounting a more targeted policy and results in timing that creates better incentives for banks. Under delayed accounting, the bank cannot choose to lever up ex ante; instead, it is allowed to increase its fundamental leverage only ex post, in the bad state of the world where it is hit with the shock.

6 Conclusion

This paper presents four facts about banks' Tobin's Q and leverage. Motivated by these facts, we propose a heterogeneous-bank model that distinguishes accounting, fundamental, and market values of bank equity and subjects banks to market constraints and book-based regulatory constraints. The novel feature of our theory is that banks delay recognition of losses on their books. Delayed accounting of losses in conjunction with the book and market constraints allows the model to reproduce the four facts.

Our model reveals several novel policy implications. We find that regulatory reforms designed to accelerate loss recognition induce a tradeoff between financial fragility and growth. This has meaningful implications for bank regulation. For example, we show that a countercyclical capital buffer can make the banking system more fragile under delayed loss accounting. Our model stresses the necessity of bridging the gap between regulatory reliance on book values and the market's focus on fundamental values to achieve a more comprehensive understanding of banking dynamics and support the design of regulatory frameworks.

A clear limitation is that we do not consider that zombie loans may actually cost the bank real resources if they have to continue funding inefficient firms to keep them alive. In turn, forcing banks to recognize losses on marketable securities may induce excessive volatility if prices are driven by speculative noise. Another limitation is that banks are treated in isolation in our model while they interact on many dimensions in the data. For example, banks have interconnected risk exposures and are subject to fire-sale externalities. Finally, we largely side-stepped the incentive issues associated with delayed accounting and meeting regulatory targets. Incorporating these features will be an important task for the future.

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