A Q-Theory of Banks*

Juliane Begenau† Saki Bigio‡ Jeremy Majerovitz§ Matias Vieyra¶

November 2024

Bank capital requirements are based on book values, which are slow to reflect losses. In this paper, we develop a dynamic model of banks to study the interaction of regulation and delayed accounting. Our model explains four stylized facts: book and market values diverge during crises, the market-to-book ratio predicts future profitability, book leverage constraints rarely bind strictly even as market leverage fans out during crises, and banks delever gradually after net-worth shocks. We show how delayed accounting can allow the regulator to achieve better outcomes than immediate (mark-to-market) accounting. In an estimated version of the model, the optimal regulation couples faster loan-loss recognition with a modest relaxation of the book leverage constraint.

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

JEL: G21, G32, G33, E44

---

*We would like to thank Youngmin Kim, Adam Su, and Mengbo Zhang for excellent research assistance. We are grateful to our discussants Dean Corbae, Miguel Faria-e-Castro, Elena Loutskina, Thorsten Koeppl, David Martinez-Miera, Adrián Pardo, and Natalya Schenck. We thank Andrew Atkeson, Haelim Anderson, Patrick Bolton, Pablo D'Erasmo, Andrea Eisfeldt, Francesco Ferrante, Mark Gertler (who also suggested the title), Kinda Hachem, Valentin Haddad, Benjamin Hebert, Arvind Krishnamurthy, Anton Korinek, Hanno Lustig, Martin Kuncl, Ken Miyahara, Gaston Navarro, Andrea Prestipino, Jose-Victor Rios-Rull, Pari Sastry, Jesse Schreger, Josef Schroth, Jeremy Stein, Robert Townsend, and Pierre-Olivier Weill for their many useful comments. We thank the conference and seminar participants of the Barcelona GSE 2021, UofT Finance Conference 2021, MFM Winter 2019 Meeting, Columbia 2020 Junior Finance Conference, Banco de Mexico, Philadelphia Fed, Federal Reserve Board, UCSD, UCSC, Michigan Ross, Northwestern University (Economics and Finance), University of Virginia, and Wharton (Macro). Previous versions of the paper circulated under the title "Data Lessons on Bank Behavior" and "Banks Adjust Slowly." The views here are ours and not necessarily those of the Bank of Canada.

†Begenau: Stanford GSB, NBER and CEPR. E-mail: begenau@stanford.edu

‡Bigio: UCLA and NBER. E-mail: sbigio@econ.ucla.edu

§Majerovitz: University of Notre Dame. E-mail: jeremy.majerovitz@gmail.com

¶Vieyra: Bank of Canada. E-mail: mvieyra@bankofcanada.ca

1 Introduction

Financial markets are quick to reflect bank equity losses. In contrast, book values are slow to recognize such losses. This difference in the speed of loss recognition leads to striking disparities between the behavior of banks' market equity and their book equity, which is reflected in Tobin's Q, the market-to-book equity ratio.[1] These differences are particularly accentuated during crises. For instance, during the 2007-2008 financial crisis—the most severe since the Great Depression—the aggregate book equity of banks remained stable while market values were eroded. Similarly, during the 2023 regional banking crisis, Silicon Valley Bank appeared well-capitalized on its books while abnormally leveraged in market value terms. Financial regulation is designed to prevent such crises but is based on accounting values. This observation raises critical questions: How does regulation constrain bank risk-taking if it is based on delayed information? What are the implications of delayed information in accounting books for an ideal regulatory framework?

To address these questions, this paper introduces a dynamic banking model emphasizing the slow recognition of accounting losses. Delayed accounting is the source of a distinction between the "fundamental" value of equity, which fully incorporates information on losses, and the book value of equity, which does not. As in other models, liquidations occur when losses cause fundamental leverage to exceed a market-determined limit. A critical aspect of our theory is that regulation intended to prevent liquidations is written in terms of accounting books. This feature allows us to analyze how the speed of loss recognition impacts bank risk-taking behavior and the effectiveness of regulation. Our theory underscores the necessity of considering the limited information in accounting books to capture bank behavior accurately and guide regulatory design.

The model features risk-neutral banks that fund risky loans with deposits and internal equity. Exogenous, idiosyncratic loan default shocks lead to jumps in fundamental leverage and observable market-based leverage.[2] These shocks can provoke market-induced liquidations. Such liquidations are socially inefficient, as they entail restructuring costs. Moreover, these social losses are not privately internalized: deposits are priced risk-free due to implicit deposit insurance, and the bank's recovery value is independent of the magnitude of the loss that leads to a liquidation. As a result, banks take excessive risk, reaping the benefits of leveraged returns without internalizing the social costs.

In our framework, bank regulation aims to correct the market's inefficiency by limiting book-based leverage. However, unlike fundamental equity, which decreases immediately upon

[1] Specifically, throughout this paper, we refer to Tobin's Q as the market-to-book *equity* ratio rather than the market-to-book *asset* ratio.

[2] The fundamental equity value differs from the market equity value because only the inside equity owner (the banker) accesses lending opportunities, leading to a valuation premium for the outside equity investor. We capture this valuation differential through differing discount rates for bankers and outside equity owners.

realizing loan losses, book equity takes time to recognize these losses. As a result of this delay, regulation constrains fundamental leverage only as past losses are slowly recognized on the books.

Our model successfully explains four facts related to the Tobin's Q of publicly traded US banks.[3] First, the time series of banks' aggregate book equity and market equity diverge substantially, especially during crises. This is a phenomenon that many models, which do not explicitly distinguish between market and book measures, cannot capture.[4] Second, Tobin's Q reflects market values, which embed forward-looking information about future profitability and risks not captured in book values. This aligns with much of the accounting literature but contrasts with models assuming no differences between book and market measures.[5]

A third fact is the difference between the cross-sectional distribution of market and book leverage: The distribution of book leverage is stable over time, to the point that, even during the 2007-2008 financial crisis, only a minor fraction of banks violated their regulatory capital ratios. By contrast, the dispersion of market-based leverage is highly volatile and rose dramatically during that period.

Finally, our fourth fact is the slow market and book leverage dynamics after net-worth shocks. We identify net-worth shocks by exploiting cross-sectional variation in banks' excess stock returns, using a factor model that partials out risk premia variation. In particular, we estimate risk-adjusted return shocks for each bank-quarter data point and use these to construct impulse responses to net-worth shocks. After a negative net-worth shock, which mechanically increases market leverage on impact, banks reduce their market leverage slowly by reducing their liabilities, with minor adjustment on the equity side. In contrast, book equity declines gradually, consistent with our delayed accounting mechanism.

Our model explains these facts not only qualitatively but also quantitatively. We estimate its key parameters using a simulated method of moments that targets the cross-sectional facts. We estimate the discount rates of investors and bankers, the size of loan default shocks, the market-based leverage constraint, and, importantly, the speed of loan loss recognition, α, a parameter whose value we modify to study policy counterfactuals regarding accounting rules. In particular, α is identified from the mean-reversion in the impulse responses of market leverage and liabilities to excess-return shocks. Our estimates also align with the

[3] In the Appendix, we show to what extent these facts are different for non-financial firms. Notably, non-financial firms have much lower leverage and are not constrained by regulatory capital ratios regarding book values.

[4] 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. Papers focusing on the effects of regulation use book equity measures (e.g., Adrian and Boyarchenko, 2013; Begenau, 2020; Adrian and Shin, 2013; Corbae and D'Erasmo, 2021; Begenau and Landvoigt, 2022). The discrepancy between both measures has led to a debate on the best way to model banks (e.g., Adrian, Etula and Muir (2014) and He, Kelly and Manela (2017)). We argue that it is important to incorporate both equity measures into the design of regulatory policies.

[5] Laux and Leuz (2010) document the flexibility of banks to account for losses.

time series of Tobin's Q and loan charge-offs.

A lesson from the paper is that because capital requirements are second-best instruments, regulators can exploit the loss-recognition speed as an additional policy tool. We capture this by allowing regulators to control α. This exercise reveals that the speed of loss recognition has costs and benefits. Delaying loss recognition can be beneficial because it allows banks hit by losses to postpone their deleveraging process, thereby reducing their need to decrease lending and alleviating the cost of stringent regulation. However, delayed accounting leaves room for banks with significant unrecognized losses to take excessive liquidation risk, potentially leading to more market-based liquidations. Because this additional tool introduces a trade-off, determining its optimal level becomes a quantitative question.

Naturally, the optimal loss-recognition speed should be determined jointly with capital requirements. We study an optimal once-and-for-all change in capital requirements and accounting rules, starting from the model's estimated steady state and considering transitional dynamics. We find that the optimal policy mix involves a slight relaxation of capital requirements from Basel III back to Basel II levels but, importantly, a substantial strengthening of accounting standards toward speedier loss recognition. The benefits of this policy change stem from lower bank liquidations. However, stricter accounting implicitly tightens effective capital requirements, so the model suggests accompanying that change with looser capital ratios. Thus, a first policy implication is that optimal *microprudential* policy should also emphasize better accounting standards and recognize their interaction with capital rules.

A second policy implication regards *macroprudential* policies. In particular, our model highlights an unintended effect of countercyclical capital buffers (CCyB). To study this macroprudential implication, we simulate a recession by introducing an aggregate shock that increases the frequency of loan losses. Surprisingly, a CCyB can increase liquidation risk, causing permanently lower lending after the recession is over. The reason is that temporarily relaxing capital requirements during a recession allows banks to increase their book leverage and, therefore, their fundamental leverage. As banks' equity risk and unrecognized losses scale with leverage, an increase in leverage can result in a wave of liquidations and depress lending through a reduction in aggregate bank equity.

As part of our investigation of macroprudential implications, we contrast the use of countercyclical capital requirements with countercyclical accounting standards. We demonstrate that relaxing accounting rules during a crisis is a better-targeted policy. A relaxation of accounting standards allows banks severely impacted by losses to postpone deleveraging while keeping capital requirements the same for unaffected banks. These policy implications suggest that accounting rules should be at the forefront of bank regulatory design.

Related Literature. Canonical macrofinance models usually employ one concept for equity.[6] 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).[7] Models with book-based constraints are motivated by questions related to 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 market and book equity differences through a delayed accounting mechanism interacting with regulatory constraints.[8] Third, we conduct policy experiments focused on how reforms to regulatory accounting rules would impact banks and the effectiveness of capital regulation.

A large literature in banking and accounting studies the impact of accounting and regulatory rules on bank behavior.[9] One strand of that literature discusses what banking activities need to be reported on the bank's balance sheet.[10] Another strand of this literature focuses on how banking activities should be reported on the balance sheet and how it affects bank decisions.[11][12] Our paper contributes most directly to the second strand of this literature. It distinguishes itself from both by using a quantitative model to analyze the optimal combination of accounting rules and financial regulation.

Our normative and macroprudential analyses relate to the literature on accounting rules

[6]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).

[7]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).

[8]Slow-moving bank leverage (Fact 4) can also be generated by other models (e.g., Brunnermeier and Sannikov, 2014; Gertler et al., 2016). The difference 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 different from leverage-ratcheting incentives (DeMarzo and He, 2021) and debt overhang (Gomes, Jermann and Schmid, 2016).

[9]See Appendix A.2.2 for an overview of the bank accounting literature. Bushman (2016) and Acharya and Ryan (2016) offer a nice survey of the literature.

[10]This relates to the debate about how stricter regulations fueled shadow banking activities' rise after the GFC (e.g., Buchak, Matvos, Piskorski and Seru, 2018; Hachem and Song, 2021; Begenau and Landvoigt, 2022; Erel and Inozemtsev, 2024; Buchak, Matvos, Piskorski and Seru, 2024; Chernenko, Ialenti and Scharfstein, 2024).

[11]For example, several papers discuss the implications of delayed loss accounting incentives and their implications empirically (e.g., Peek and Rosengren, 2005; Caballero, Hoshi and Kashyap, 2008; Blattner, Farinha and Rebelo, 2023; Plosser and Santos, 2018; Flanagan and Purnanandam, 2019). Milbradt (2012) theoretically studies the effect of fair-value accounting rules on banks' trading behavior.

[12]Studies of the economic effects of zombie lending practices include Faria-e Castro, Paul and Sánchez (2024), Acharya, Lenzu and Wang (2021), and Acharya, Crosignani, Eisert and Eufinger (2024).

and their effects on financial stability and credit supply, where we find that accounting rules should optimally be set jointly with capital requirements.[13] Our model, however, abstracts from banks' ability to manipulate accounting rules to their advantage.[14] To our knowledge, our 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.[15]

Finally, our paper relates to a growing literature emphasizing bank heterogeneity as an important dimension of bank regulation (e.g., Corbae and D'Erasmo, 2021; Rios-Rull, Takamura and Terajima, 2023; Goldstein, Kopytov, Shen and Xiang, 2024; Begenau, Landvoigt and Elenev, 2024; Abad, Bigio, Garcia-Villegas, Marbet and Nuno, 2024). The novelty here is that we emphasize accounting standards as an important dimension of capital regulation beyond capital requirements. Our focus on additional dimensions to bank regulation is also shared with Corbae and Levine (2024), which investigates the role of competition.

2 Motivating Facts

In this section, we document four stylized facts that motivater our Q-theory.

Data. We construct a panel of banks using balance sheet and income statement data 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.

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

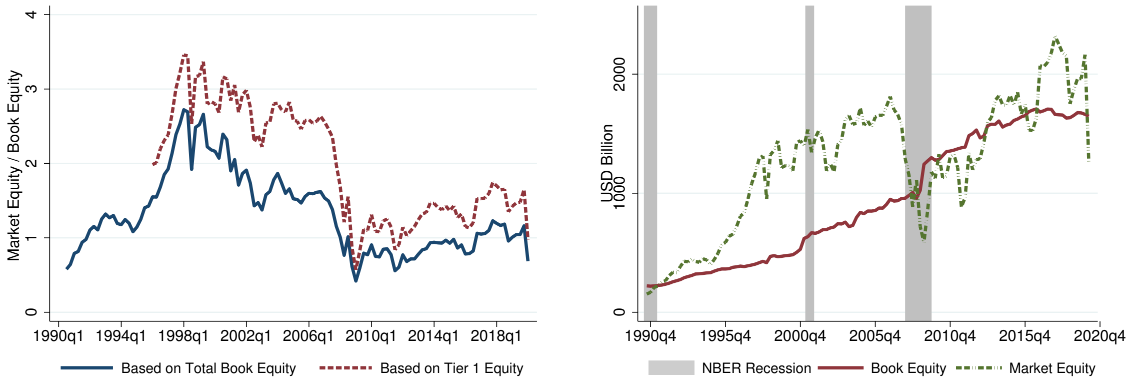
[13] In response to the financial crisis, the procyclical effects of mark-to-market assets were discussed (e.g., Shleifer and Vishny, 2011; Laux and Leuz, 2010; Plantin and Tirole, 2018). In response to the COVID-19 crisis, the extent of regulatory forbearance took center stage in macroprudential policy 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).

[14] 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. Behn, Haselmann and Vig (2022) and Haselmann, Sarkar, Singla and Vig (2022) study important political economy issues of financial regulation and adherence to accounting rules that we abstract from.

[15] 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. All level variables are converted to 2012 Q1 dollars with the seasonally adjusted GDP deflator.

over book equity—fluctuates widely over time.[16] 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.[17] Panel (b) shows the components of aggregate Tobin's Q across all BHCs. Market valuations often diverge from book valuations, especially during financial crises. For example, during the 2008/2009 financial turmoil, aggregate book equity looked unaffected by the crisis, 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 equity ratio and future cash flow, controlling for time fixed effects, the Tier 1 regulatory capital ratio, and log book equity.[18] Panel (a) demonstrates Tobin's Q as a predictor of next

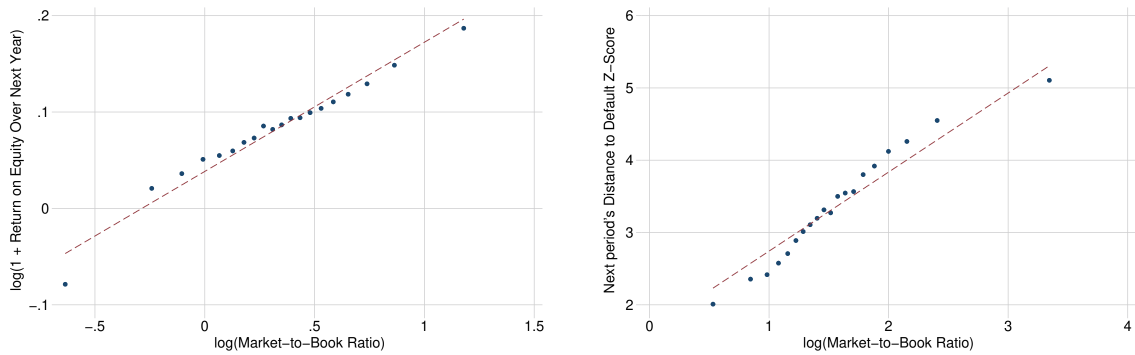
[16] Book and market equity differences during the GFC have been documented before (see, for example, Adrian and Shin, 2010; He et al., 2017). Our paper proposes a theory based on delayed loss accounting as a mechanism to explain the dynamics of bank Tobin's Q.

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

[18] To control for covariates, we residualize the left- and right-hand-side variables on the controls and then

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

(a) Return on Equity (b) Distance to Default



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, the Tier 1 capital ratio, and quarter fixed effects. 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 $\frac{\log(V/D)+\mu_V - \frac{1}{2}\sigma_V^2}{\sigma_V}$ (see Duffie, 2022). 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.

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 recognizing cash flow shocks in accounting values.

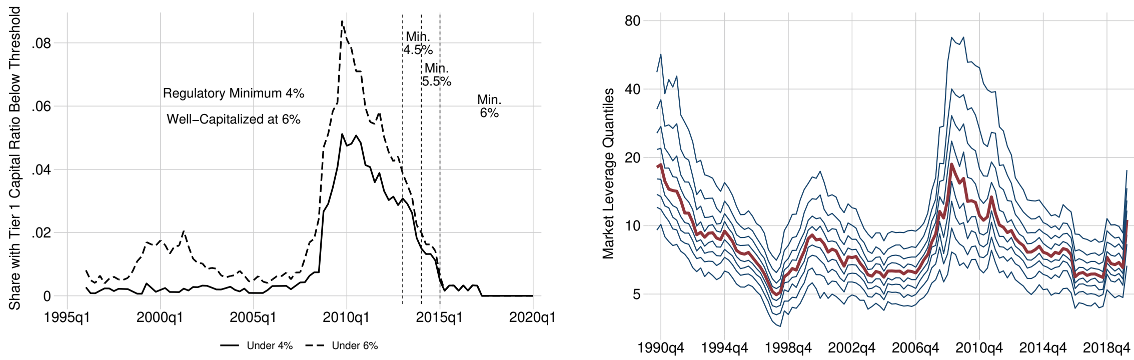
Motivating Fact 3: Regulatory Constraints Rarely Bind Strictly, and Market-Based Leverage Fans out During Crises. Our third stylized fact clarifies the nature of banks' leverage constraints. Panel (a) of Figure 3 presents the fraction of banks whose Tier 1 capital ratio falls below different cutoff values 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 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,

add back the mean of each variable to maintain the centering. Controlling log book equity is important to prevent spurious results due to ratio bias (see Kronmal, 1993).

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 Appendix A.2.1. 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 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.[19]

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 for nonfinancial firms than for banks. The literature has rationalized high bank leverage as a result of deposits providing liquidity services, as well as government guarantees that implicitly subsidize bank deposits. Banks' incentive to carry high leverage, potentially in

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

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. Shocks create a persistent gap between 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,[20] 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 mean-zero 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 the response to a unit shock in $\varepsilon_{i,t}$. That is, the IRF is defined as

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

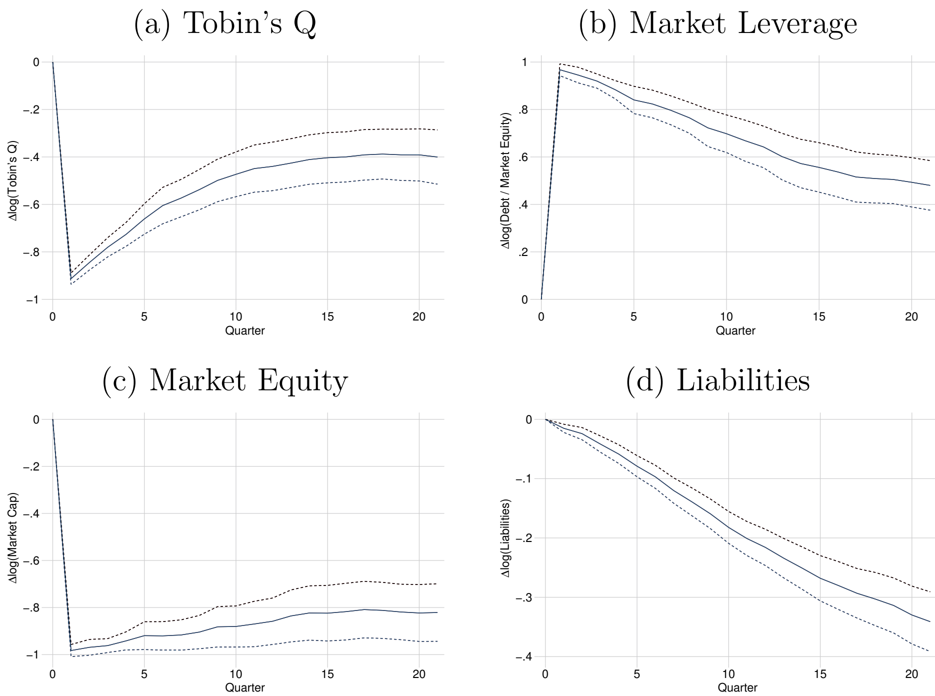
We interpret the shocks, $\varepsilon_{i,t}$, as idiosyncratic shocks to the bank's net worth, reflecting changes in expected cash flows. In our model, we show that these shocks follow from loan defaults. To estimate these net-worth shocks, we use shocks to banks' excess stock returns—see Appendix Section 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 identify these shocks empirically, $\varepsilon_{i,t}$, and isolate them from shocks to (a) the discount rate (risk premia) or (b) future investment opportunities.

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

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

each bank as in Gandhi and Lustig (2015).[21] 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).[22] We conduct various 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 1, the cumulative response one quarter later ($-\beta_0 - \beta_1$) as quarter 2, and so on. Dashed lines denote the 95% confidence interval. Standard errors are clustered by bank. The panels display the impulse responses of log Tobin's Q in Panel (a), log market leverage in Panel (b), log market equity in Panel (c), and 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. In Panel (c), market equity falls immediately by approximately 1% on impact and recovers to -0.8% after four years, remaining stable thereafter. Book equity declines slowly, reaching -0.5% only after 10 quarters (see Panel (f) in Appendix Figure A.4). These results imply that net worth shocks that are immediately recognized in market equity are only slowly recognized on

[21] 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.

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

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.

In Appendix Section B.4, we examine heterogeneity in impulse response functions across banks. We do not find robust evidence of heterogeneous impulse responses; however, we have limited statistical power to pick up these differences.

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 with unit mass funds 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:

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

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 defaults.

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.

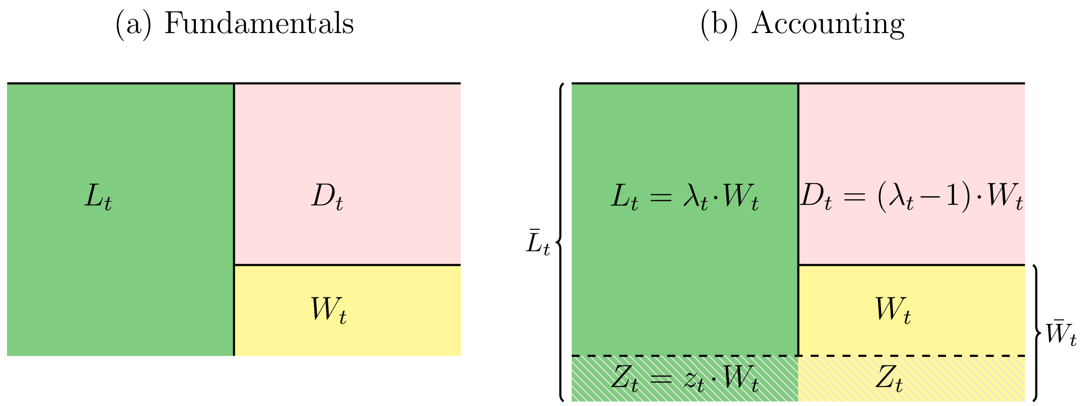
Equity Definitions, Accounting Rules, and Zombie Loans. We distinguish between three forms of equity: the fundamental value encountered above, W; the book (or accounting) value, $\bar{W}$; and the market value, S. Book equity $\bar{W}$ differs from fundamental equity W. Whereas fundamental equity immediately 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" in the sense that they will not yield income going forward.

Figure 5 sketches the bank's fundamental balance sheet in Panel (a) and accounting balance sheet in Panel (b). 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.[23]

[23] $\lambda - \bar{\lambda} = (\lambda - 1) z / (1 - z) \geq 0$ 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)).

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 return on equity.[24] 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 equity ratio S/W and the fundamental-to-book equity ratio, 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 excess stock-return shocks analogous to those in the data. Whereas book equity and market equity have data counterparts; the fundamental value does not.

Informational Assumptions and Timing. Banks face the possibility of market and regulatory liquidations. Market discipline induces liquidations if fundamental leverage λ exceeds an upper bound κ. Regulators liquidate 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.

[24] 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 $\frac{c}{\rho^I - (\text{ROE} - c)} W$ via the Gordon growth formula. This will equal W only if $\text{ROE} = \rho^I$.

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

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

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 $z < z^m \equiv (\kappa - \Xi)/(\Xi - 1)$. Note that a higher zombie ratio decreases book leverage, therefore effectively relaxing the constraint in terms of fundamental leverage.

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 they do not control their leverage at the moment of a loan default. Hence, it is important to understand how the variables in constraint (5) jump when a default event occurs; liquidations are triggered when these variables jump to a point where the constraint is violated.

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:

$$\lambda + J^{\lambda} \equiv \frac{\overbrace{L - \varepsilon L}^{\text{loans after default}}}{\underbrace{W - \varepsilon L}_{\text{equity after default}}} = \frac{\lambda(1-\varepsilon)}{1-\varepsilon\lambda} \leq \kappa. \tag{6}$$

Because fundamental leverage jumps to $\lambda + J^{\lambda}$ at the moment of a default, leverage may violate (5). 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 immediately offset the jump in leverage by selling assets. In technical terms, leverage is non-adapted—it jumps at the instant of a default event and then reverts. This is the analog 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 a lack of compliance whenever the bank is provably violating the regulatory limit. Thus, banks are liquidated by the regulator if the following condition is violated:

$$\bar{\lambda} + J^{\bar{\lambda}} \equiv \frac{\overbrace{\bar{L} - \varepsilon L}^{\text{book loans after default}}}{\underbrace{\bar{W} - \varepsilon L}_{\text{book equity after default}}} = \frac{\lambda(1-\varepsilon) + z}{1 - \varepsilon\lambda + z} \leq \Xi. \tag{7}$$

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 a 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 non-adapted process. We discuss the motivation for our informational assumptions in greater detail below.

If regulators were oblivious to bank losses, Equation (7) would not include default losses and Z_t would be adapted. 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. 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:*

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

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

The formula for $\Lambda(z)$ shows that, for $z \leq z^s$, a larger z allows banks to lever up safely, avoiding regulatory liquidations. 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. 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:

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

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 faster 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 to solve a Hamilton–Jacobi–Bellman (HJB) equation.

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

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

subject to the law of motion of fundamental equity, (2), and the law of motion of zombie loans, (8).

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 the 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 condition 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 liquidation unless they have a strictly positive benefit from doing otherwise.

Discussion of Model Assumptions. Our model incorporates several financial frictions: First, consistent with the intermediary asset pricing literature (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014), bank equity can only grow through retained earnings. Second, depositors do not internalize bank liquidation risk in their pricing. This reflects implicit deposit insurance (Diamond and Dybvig, 1983) or government guarantees (Kelly, Lustig and Van Nieuwerburgh, 2016; Atkeson, d'Avernas, Eisfeldt and Weill, 2018). Finally, the solvency condition (5) forces liquidations and is shaped by market forces and regulatory considerations.

While recent banking models, such as Gertler and Kiyotaki (2015), impose constraints on market-valued leverage, our framework models market-based liquidations that depend on fundamental leverage. This approach builds on the rich corporate finance literature, e.g., Leland and Toft (1996), where once fundamental leverage exceeds a multiple, the firm is voluntarily closed. Deposit insurance and regulatory constraints tailor this model to the banking sector.

Delayed loss accounting, the novel feature, 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). Banks create zombie loans by delaying charge-offs, avoiding reductions in regulatory capital. Since rolling over a loan does not require new funds, evergreening allows a bank to inflate its accounting equity. The effect is to relax the leverage constraint (5).

We further assume that bank equity prices contain information not in books. This aligns with the empirical findings in Section 2 suggesting that Tobin's Q contains more predictive power than book values. This information can be collected by analysts forecasting a bank's loan portfolio defaults based on sources other than the bank's books.

Our model makes two critical assumptions that shape the regulatory environment: First, regulators cannot close banks based on market data. To liquidate banks, regulators must intervene in the bank and build accounting-based evidence. This assumption is grounded in the legal constraints faced by regulators. Second, we assume that banks need time to conceal their losses. The assumption that losses cannot be hidden instantaneously reflects that evergreening requires time-consuming loan reprogramming. Likewise, moving assets from market to hold-to-maturity accounts takes time. As a result, the regulator only has a short window of opportunity to intervene upon the realization of default. Once losses are hidden, regulators cannot build a case for liquidation. The assumption also makes the bank vulnerable to regulatory liquidations if it takes excessive leverage.

The combination of both assumptions allows the model to feature both regulatory-liquidations risk and hidden losses parsimoniously. If regulators could never obtain evidence of bank losses, regulation would be immaterial. In turn, if regulators could constantly intervene banks there would be no scope for delayed accounting.

In principle, one could argue that regulators can constantly intervene banks to prevent them from hiding any losses. However, this argument would miss that regulatory interventions entail fiscal costs and unwarranted interventions risk provoking a regulatory backlash. This is why we assume that regulators intervene only when they know, possibly through market prices, that the bank violates the regulatory constraint. To elaborate on this point, in Appendix D.8, we present a simple sequential-form game based on costly state verification, in the spirit of Townsend (1979), consistent with this notion.[25] We contend that the informational and timing assumptions mirror the events of the regional banking crisis in 2023.[26]

The normative analysis introduces another friction: social liquidation costs, which are critical to justifying the need for regulation. Regulatory violations must lead to bank closures to ensure compliance. In our model, social liquidation costs are assumed to be identical for both market-based and regulatory liquidations. This assumption highlights why capital requirements are not a first-best instrument, paving the way for the policy tradeoffs analyzed in Section 5. Exploring optimal penalties for enforcement and distinguishing between the social costs of different liquidations lies beyond the scope of this paper.

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.

[25]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.

[26]Notably, they mirror the dissolution of SVB in 2022 Q3: Despite being insolvent, that 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 market values. This discrepancy allowed a significant portion of SVB's securities holdings to appear inflated to meet regulatory standards. The regulator acted after the bank's stock valuation plummeted.

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,*

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

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.[27] Since the objective is piecewise linear, with a discontinuity, optimal leverage is either at the shadow or the liquidation boundary:

$$\Omega^* = r^D + \max\left\{\Lambda\left[\left(r^L - r^D\right) - \sigma\varepsilon\right],\ \left(r^L - r^D\right)\kappa - \sigma\left(1 - \frac{v_o}{v}\right)\right\}.$$

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

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

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

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

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

constraint Ξ. Thus, the optimal leverage, as outlined in Corollary 1, generalizes to:

$$\lambda^*(\Xi,\kappa) = \begin{cases} \min\{\kappa,\Xi\}\left(1+\varepsilon\left(\min\{\kappa,\Xi\}-1\right)\right)^{-1} & \text{if } \min\{\kappa,\Xi\} \le \lambda^o \\ \\ \min\{\kappa,\Xi\} & \text{if } \min\{\kappa,\Xi\} > \lambda^o. \end{cases} \tag{13}$$

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 also estimated an alternative version with adjustment costs only. That model required implausibly high adjustment costs to explain the slow dynamics of leverage. Our delayed accounting mechanism provides a more plausible microfoundation for a "reduced-form" adjustment cost, producing slow-moving dynamics.

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:*

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

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

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

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

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:*

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

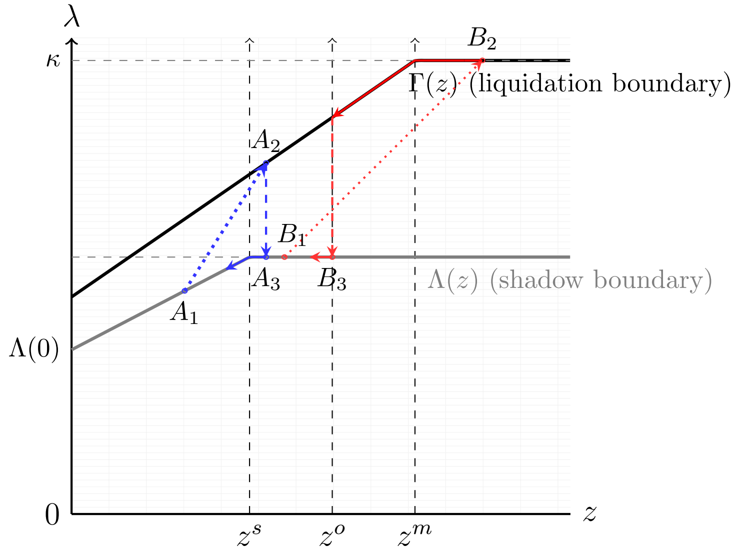
As with immediate accounting, under delayed accounting, leverage λ^* is a bang-bang control. It is at either the shadow or the liquidation boundary. The difference is that the solution depends on z. The intuition is the same. Banks risk liquidation when the returns Ω sufficiently counterbalance their 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 $\Omega(z^o, \Gamma(z^o)) = \Omega(z^o, \Lambda(z^o))$.[28]

We use Figure 6 to explain the dynamics implied by Corollary 2. The points $\{A_1, A_2, A_3\}$ and $\{B_1, B_2, B_3\}$ are part of different trajectories in the $\{z, \lambda\}$-space. Consider a bank that receives a default shock starting at A_1. Before the shock, the bank sets leverage at the shadow boundary. In the absence of adjustment by the bank, the loan default would lead to a jump from A_1 to A_2: since the bank was on the shadow boundary before the shock, the shock puts it onto the liquidation boundary. The bank remains solvent. Because the zombie loan ratio 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, arriving at A_3 the instant after the shock. 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 B_1, the dynamics change. From that point, the shock pushed the bank to B_2 (note that since the bank starts to the right of z^s, where the market constraint is binding for the shadow boundary, the point it jumps to is to the right of z^m, where the market constraint binds for the liquidation boundary). Since the zombie loan ratio is higher than z^o, the bank opts to stay at the liquidation boundary, risking closure if it is hit by another shock. Provided that no further loan default events occur, the bank travels

[28] 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 typical trajectories under delayed accounting, as characterized in Proposition 2. The dashed vertical lines correspond to z^s (the point at which the market constraint becomes binding for the shadow boundary), z^o (the level of the zombie loan ratio above which a bank chooses to stay at the liquidation boundary and risk closure), and z^m (the point at which the market constraint becomes binding for the liquidation boundary). The blue trajectory shows the path of a bank starting at A_1 after it is hit with a shock; because the shock does not push the bank past z^o, it immediately delevers back to the shadow boundary. The red trajectory shows the path of a bank starting at B_1: after it is hit with a shock, it stays at the liquidation boundary and only returns to the shadow boundary once its zombie loan ratio drifts down to z^o.

left along the liquidation boundary as books slowly recognize the loss. Once z reaches z^o, the bank chooses to delever to return to the shadow boundary at B_3.

Next, we turn to Section 4, 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, book and market equity diverge due to the presence of zombie loans (Fact 1). Those zombie loans are gradually recognized on the books, making future book losses predictable (Fact 2). For appropriate parameters, most banks stay at the shadow boundary, maintaining a book leverage that is away from the liquidation boundary even if their market leverage is high (Fact 3). Because losses are recognized slowly, the bank delevers slowly in response to a negative shock (Fact 4).

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 tradeoff between returns and liquidation risk. Dividend smoothing allows us to match the IRFs more closely. 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 $1/\theta$.[29] 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.

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	
$\rho = 2.02\%$	Banker's discount rate	Book equity growth rate: 2%
$\rho^I = 3.45\%$	Investor's discount rate	Market-to-book ratio of equity: 1.316
$\theta = 6.69$	Banker's inverse IES	Market leverage IRF
$\varepsilon = 1.24\%$	Loan loss rate in event of default	Mean book leverage
$\alpha = 4.34\%$	Speed of loan loss recognition	Liabilities IRF
$\kappa = 50.37$	Market-based leverage constraint	Liabilities IRF
$\sigma = 0.105$	Arrival rate of loan default shocks	Mean quarterly net charge-off rate of 0.12%
$v_o = 0.037$	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.

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, the book

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

equity growth rate, the market-to-book equity ratio, and the IRFs of bank liabilities and market leverage.[30] We require the model to match the charge-off rate and bank failure rate exactly.[31] We choose the arrival rate of the loan default shock to match a 0.12% quarterly net loan charge-off rate, setting $\sigma = 0.105$. We choose v_o, the banks' liquidation value, to match a quarterly bank failure rate of 3.65 basis points based on FDIC data.[32]

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 2.02%. To estimate investors' discount rate ρ^I, we target the average market-to-book ratio.[33] 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 $\rho^I = 3.45\%$.[34]

We use the IRF of market leverage as a target for θ.[35] Since dividends affect the market value of the bank, the IRF of market leverage to a net-worth shock is informative about θ. We estimate $\theta = 6.69$, 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 $\varepsilon = 1.24\%$ 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, fundamental leverage jumps and reverts with the reversion rate in z. Hence, the mean reversion in the IRF for liabilities $D = (\lambda - 1)W$ is informative about α, which

[30] 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.

[31] 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.

[32] See the FDIC website here.

[33] 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.

[34] 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, the banker's effective discount rate is $\rho + \theta \cdot \Omega^W = 0.0202 + 6.69 \cdot 0.02 = 15.4\% >> 3.45\% = \rho^I$.

[35] Since we also target the IRF for liabilities and log market leverage is defined as the difference between log liabilities and log market equity, this is equivalent to targeting the IRF of market equity.

we estimate to be 4.34%. 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 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.[36] To back out a shock time series that mimics the global financial crisis (GFC), we subject the values of three parameters, σ, α, and v_o, to an unanticipated 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%.[37] 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 in Table 1. Specifically, we first assume that the arrival rate of loan default shocks σ jumps from the estimated value of 0.105 to $\sigma^{GFC} = 0.516$ between 2007 Q3 and 2009 Q4. After 2009 Q4, the arrival rate jumps back to $\sigma = 0.105$. Second, we assume that the speed of loss recognition jumps from the estimated value of $\alpha = 4.34\%$ to $\alpha^{GFC} = 10.09\%$ in 2007 Q3 and remains at this level until 2019 Q4, after which it reverts to α.[38] 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 the bankers' outside option, the liquidation value, from its calibrated value of

[36]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.

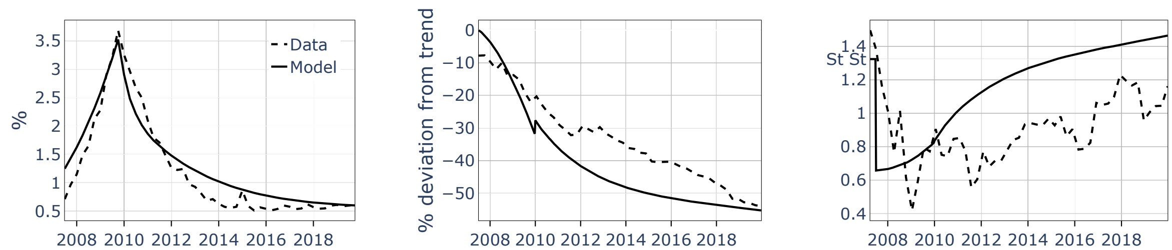
[37]Based on FDIC data, 548 banks failed between 2007 and 2019, almost all of them before 2012, and there were 7288 banks in 2007. Thus, we target a cumulative bank failure rate of 548/7288=7.52%.

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

$v_o = 0.037$ to a value over the period 2007 Q3 to 2019 Q4 of $v_o^{GFC} = 0.01$. [39] Panel (a) of

Figure 7: Crisis and Recovery in Model and Data

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



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 net charge-off rates (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.

Figure 7 shows that these parameter assumptions generate a good fit of the aggregate net charge-off rate series. We also closely hit the cumulative bank failure rate at 7.59% 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.[40] 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. Panel (c) of Figure 7 plots the time series of Tobin's Q, the ratio of market equity to book equity, in the data (dashed line) and compares it to that in the model with aggregate shocks (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 predominantly by little q, the ratio of fundamental equity to accounting equity; we do not assume changes in investors' discount rate ρ^I. 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.

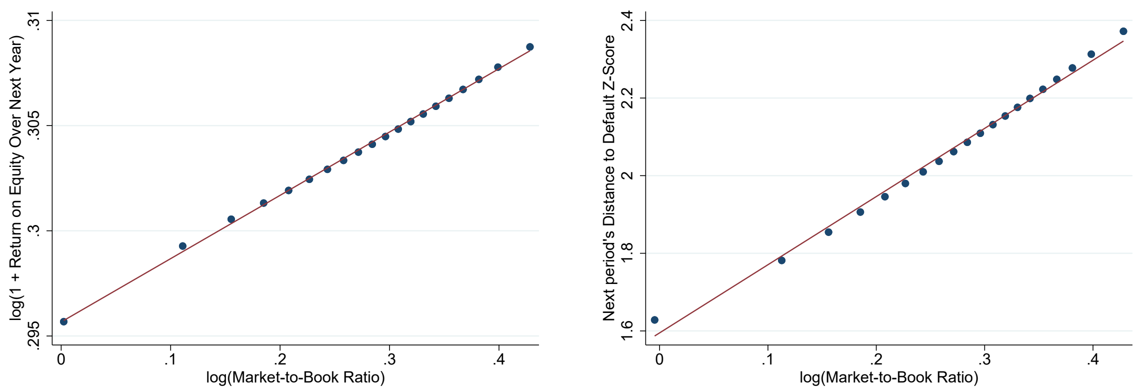
[39] The reason we need a lower v_o is that a higher loan default arrival rate and higher loan loss recognition rate would result in too many bank failures. Lowering v_o reduces the attractiveness of bankruptcy.

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

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.

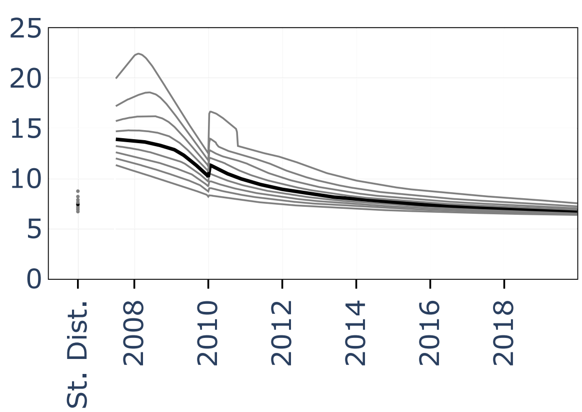
Figure 8: Predictability (Fact 2)

(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.

Figure 9: Market Leverage Dispersion (Fact 3)



Notes: This figure shows the distribution of market leverage for model-simulated data in response to the same aggregate shocks 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.

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 are far from the market leverage constraint, which allows for 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 aggregate shocks to the three parameters as discussed above, 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 to its estimated value of 0.105, 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).[41] 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 close to 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 data.

4.3 Effects of Accounting Rules

The Current Expected Credit Loss (CECL), a new accounting standard, went into effect for all financial institutions in 2023. Most publicly traded banks have had to adhere to CECL accounting since January 2020, though the Coranavirus pandemic gave those banks an option to delay. 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

[41] 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. (72). 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 one by -1%, and compute the IRF at horizon h as the sum of the coefficients up to lag h.

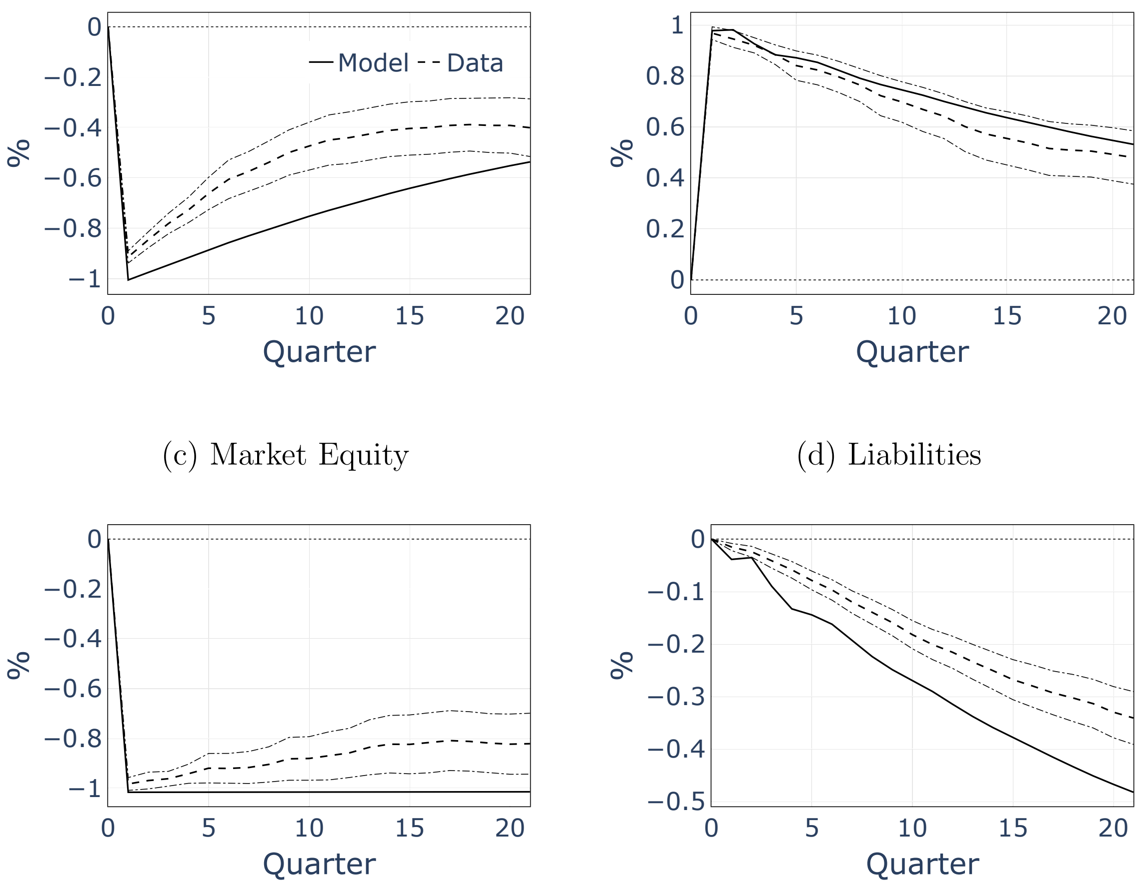
Figure 10: Model vs. Data Impulse Responses (Fact 4)

(a) Tobin's Q

(b) Market Leverage

(c) Market Equity

(d) Liabilities

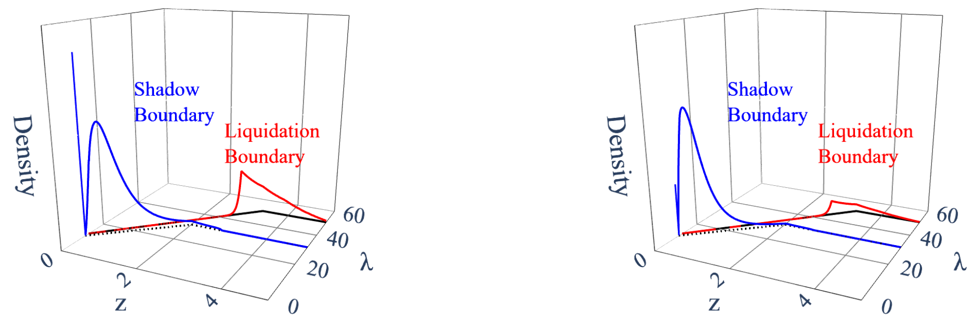


Notes: The figures present the impulse response functions of model-simulated data (solid line) for the benchmark calibration and compares them to those from the data (the dashed line represents the point estimates and the dash-dot lines the 95% confidence interval). We show the impulse response function 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. (72). 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.

an accounting reform in the spirit of CECL, i.e., which accelerates the speed of loan loss recognition, features a tradeoff.

Figure 11: Comparison of Stationary Distributions for Different α

(a) Baseline Parameters: $\alpha = 4.34\%$ (b) Faster Recognition: $\alpha = 6\%$

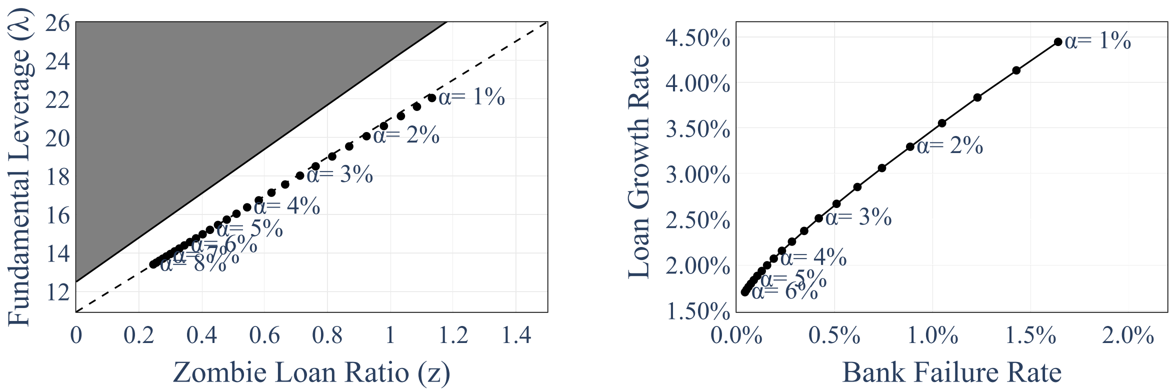


Notes: This figure presents a two-dimensional plot of the stationary distribution of banks across fundamental leverage λ and the zombie loan ratio z. The black dashed line traces out the shadow boundary $\Lambda(z)$ and the solid black line the liquidation boundary $\Gamma(z)$. The blue and red lines 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 of 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: Steady States for Different α: 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 10.92 with $\alpha = 1\%$ to 10.96 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 tradeoff 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.[42] We assume the social cost of liquidation is large enough that risking liquidation is never socially desirable:

Assumption 2 *Risking liquidation is 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:

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

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

[42] 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-best leverage and second-best regulation 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:*

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

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:*

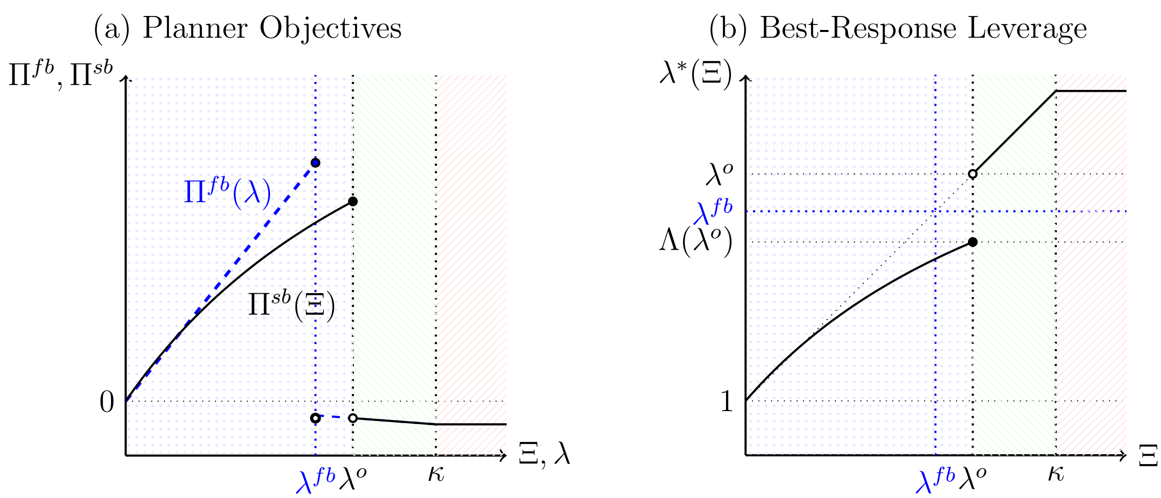
$$\Pi^{sb} = \max_{\Xi} \underbrace{\left(r^L - r^D - \sigma\left[\varepsilon + (1-\psi)(1-\varepsilon)\mathbb{I}_{[\lambda^*(\Xi,\kappa)>\Lambda]}\right]\right)}_{\textit{social return of leverage}} \lambda^*(\Xi,\kappa). \tag{18}$$

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

2.b. Second Best: Capital Requirements. *If under laissez faire banks risk liquidation, $\kappa > \lambda^o$, then 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, $\kappa \leq \lambda^o$, 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 regulatory enforcement mandates socially inefficient liquidation. Figure 13 shows this in detail. In Panel (a), the dashed curve represents the first-best objective function, Π^{fb}, as a function of leverage, λ. This curve increases up to the first-best leverage, λ^{fb}, and turns negative beyond that point. The negative values arise because risking liquidations is socially suboptimal. As a result, λ^{fb} is the shadow boundary of the market-based leverage constraint (κ), the maximum leverage that avoids the risk of default.

The solid curve in Panel (a) depicts the planner's objective function under the second best, $\Pi^{sb}(\Xi)$, which is plotted as a function of the capital requirement, Ξ, instead of λ. The second-best objective has Ξ as an argument because regulation does not control leverage directly but instead influences it through the banks' best response to the capital requirement. Panel (b) shows the bank's best-response leverage $\lambda^*(\Xi)$: Banks set their leverage at the shadow boundary when $\Xi \leq \lambda^o$, and at the liquidation boundary when $\Xi > \lambda^o$.

The graph of Π^{sb} in Panel (a) is determined by the best response $\lambda^*(\Xi)$. If the regulator sets $\Xi > \lambda^o$, banks risk liquidation, leading to a socially inefficient outcome and a negative value for Π^{sb}. The regulator must ensure $\Xi \leq \lambda^o$ to prevent such liquidations. However, when $\Xi \leq \lambda^o$, banks keep a capital buffer and set their leverage at the shadow boundary of Ξ. This buffer prevents the implementation of first-best leverage. Consequently, the second-best outcome satisfies $\Pi^{sb}(\lambda^o) < \Pi^{fb}(\lambda^{fb})$ in the region without liquidation.

The optimal capital requirement, Ξ, is therefore set to λ^o, inducing banks to set leverage at $\Lambda(\lambda^o)$, which is the shadow boundary corresponding to λ^o. This choice maximizes second-best leverage while avoiding liquidation risks.

Intuitively, capital requirements are second-best instruments because they rely on regulatory enforcement that mandates liquidation if banks breach the imposed limit. This enforcement mechanism compels banks to hold excess capital as a buffer, reducing lending compared to the first best. Despite this inefficiency, capital requirements are superior to a laissez-faire approach. Next, we show that, beyond providing a good description of the dynamics of Tobin's Q and leverage, delayed accounting is a valuable additional regulatory tool.

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:

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

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

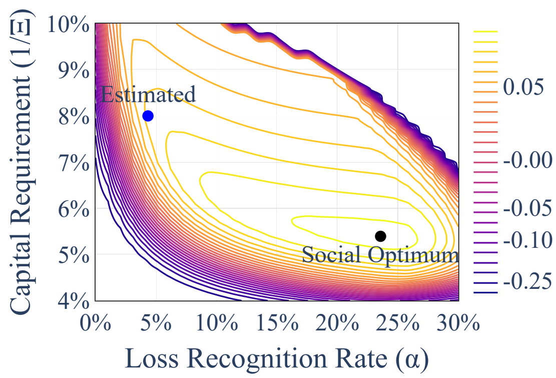
The socially optimal $\{\alpha, \Xi\}$-mix maximizes the g_0-weighted average of the social value of an individual bank, $p(z)$. The function $p(z)$ is the present value of bank payouts. Notice that the social value is isomorphic to the private value, except that the planner internalizes the liquidation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

5.2 Microprudential Implications: Optimal Regulation

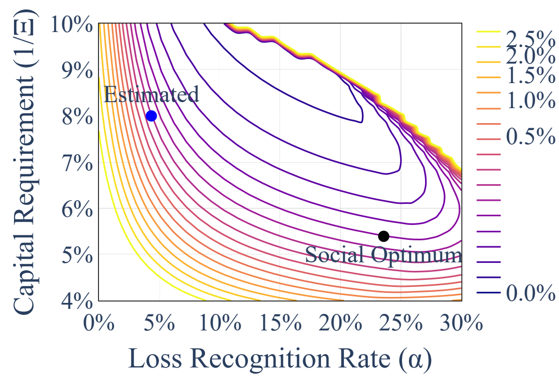
In this subsection, we study the microprudential policy implications of our model and derive the optimal combination of $\{\alpha, \Xi\}$ numerically using our estimated model. This also allows for a normative assessment of speedier loss recognition rules, as implied by the recent move to the CECL accounting 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

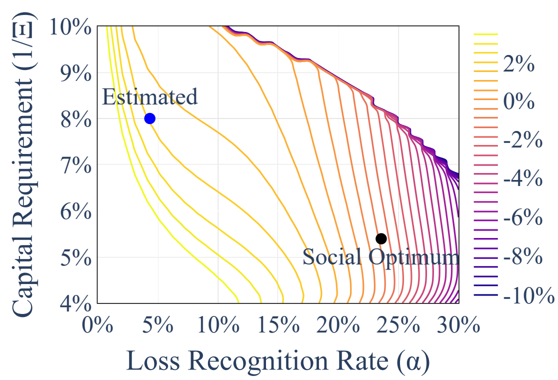
(a) Welfare



(b) Bank Failure Rates



(c) Loan Growth Rates



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 -2.89%, which we hold constant across new combinations of $\{\alpha, \Xi\}$.[43]

Figure 14 summarizes the results. It presents contour plots for welfare in Panel (a), bank failure 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 96 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 23.6% at the optimum, compared to the baseline estimated value of 4.34%. To put these numbers in perspective, the reform would bring the half-life of zombie loans from four years to just over a year. 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 5.4%, closer to the requirement under Basel II.

To understand what drives these welfare gains, we note that social welfare $\mathcal{P}(\alpha, \Xi, \{g_0\})$ is well approximated by the following aggregate bank moment[44]:

$$\mathcal{P}(\alpha, \Xi, \{g_0\}) \approx \frac{\mathcal{C} - \mathcal{S}}{\rho - (\mathcal{G} - \mathcal{C})}.$$

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., $\mathcal{S} \approx 2.89\%$. 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 $\alpha = 4.34\%$, 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

[43] 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 $-1.17/\rho = -1.17/0.0202$. Multiplying the liquidation rate of 0.05% by the annuity value translates the cost into a flow cost of -2.89% per year.

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

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 2.89% to 0.94%. While banks would appear more levered under the reform—book leverage would increase from 10.96 to 15.24—this change is only cosmetic, as fundamental leverage increases only slightly from 15.92 to 16.8. Relaxing the bank capital requirements increases banks' ROE, $\mathcal{G}$, by approximately 1.8 p.p. 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 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 $\mathcal{G}$.[45]

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) a constant capital requirement and delayed accounting as estimated in Section 4, (ii) a countercyclical capital buffer (CCyB) in the presence of delayed accounting, and (iii) a countercyclical accounting rule.[46] Our findings indicate that delayed accounting can lead to unintended consequences when a CCyB rule is imposed. Under delayed accounting, a relaxation of regulatory limits on leverage during crisis times can increase the risk-taking of banks and lead to more bank failures in the long run.[47] By contrast, relaxing accounting rules during a loan default crisis leads to fewer bank failures in our model.

We study the effects of a CCyB rule in our model by first simulating a boom during which the capital requirement tightens and then a bust during which the capital requirement is relaxed. To simulate a boom in our model, we introduce a time-varying loan default arrival

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

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

[47] 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."

rate that is half the estimated value of $\sigma = 0.115$ at the peak of our simulated boom:

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

We choose the scalar τ such that σ_t is one-half of our estimated $\sigma = 0.115$ at the boom's peak, six quarters after banks learned about the shock. The scalar η governs the persistence of the shock that we choose such that, in the absence of other shocks, σ_t returns to its estimated steady-state value in approximately five years.[48] Six quarters into the boom simulation, at the peak, we hit banks with a second shock (at $t = 0$) that captures suddenly deteriorating credit conditions. We model a crisis as following a boom, where the probability of loan default shocks σ_t doubles to $2 \times \sigma$ over six quarters. Notably, at the onset, banks do not know that a crisis will happen at the boom's peak. In the figure, the boom shock hits banks at $t = -6$, and the crisis shock hits banks at $t = 0$.

Figure 15 shows how aggregate lending (left column) and bank failure risk (right column) respond to an aggregate shock under three policy regimes during the credit crisis and its aftermath. In all exercises, we do not replace failed banks, motivated by the idea that there is little bank entry during a banking crisis. Note that we plot aggregate loans as percentage deviation to the boom's peak at $t = 0$. The solid lines of the graphs in the left column represent the percentage deviation of aggregate loans from steady-state trend growth. The graphs in the right column show the fraction of banks operating at the liquidation boundary. We distinguish between "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).[49]

The top row presents the results for our baseline policy regime of a constant capital requirement Ξ and delayed accounting based on our estimation. The credit crisis leads to a slow decline in aggregate lending (left panel) because a larger mass of banks moves to the liquidation boundary (right panel), where failure is imminent. Since failed banks lose their equity capital, aggregate credit supply declines since it equals levered aggregate equity.

In the middle row of Figure 15, we analyze a CCyB regime, which we model as a time-varying Ξ_t:

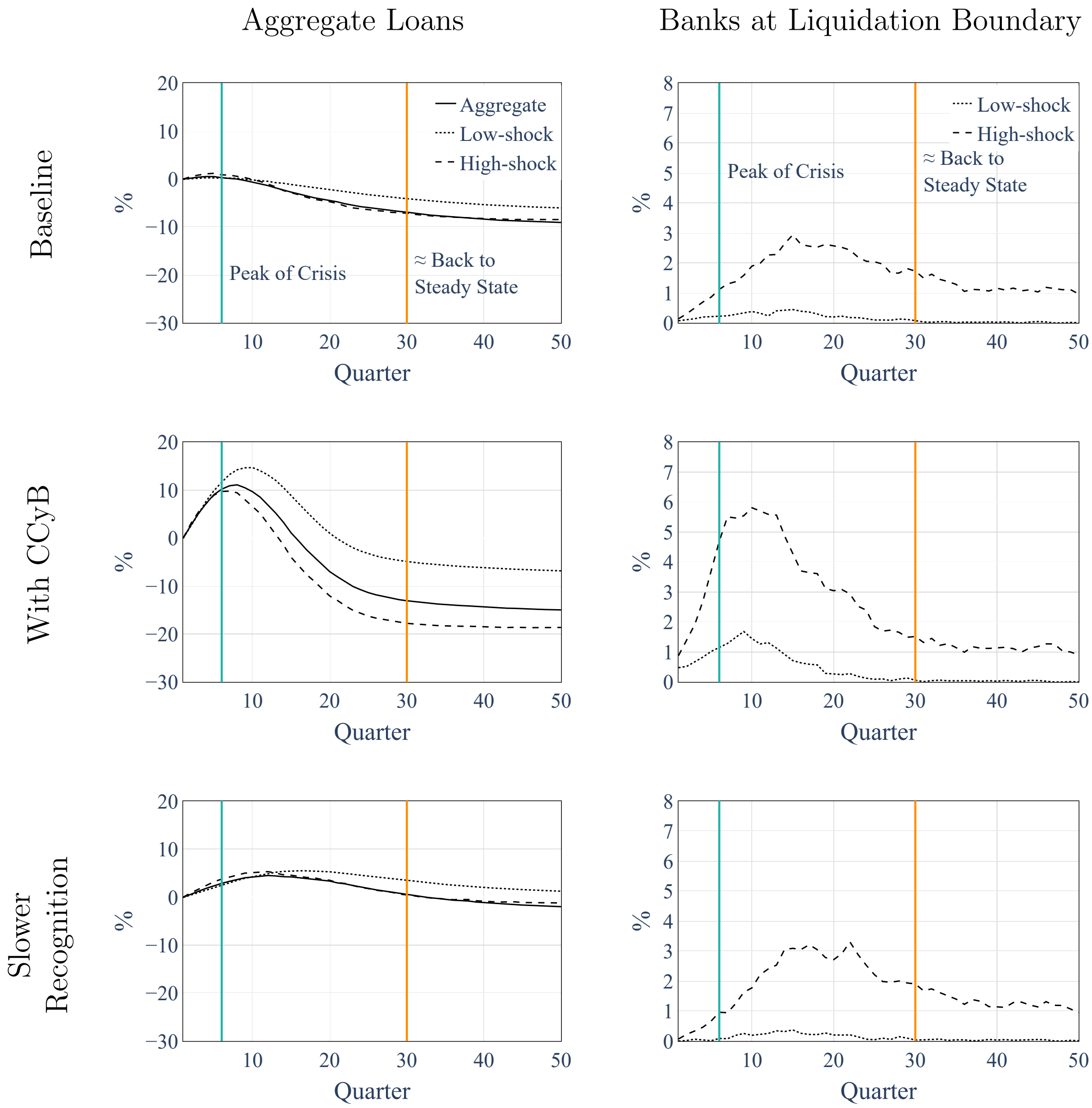
$$\Xi_t = \Xi \left(1 + \left(\frac{\Xi^{CCyB}}{\Xi} - 1\right)\exp(-\eta(t-\tau)^2)\right). \tag{21}$$

We choose the same values for η and τ as in Eq. (20), starting from the boom, where the capital constraint is progressively tightened from 8 to 10% during the boom period (quarters one through six), and then subsequently relaxed to 6% during the credit crisis.

[48]We start the simulation at the stationary distribution. Banks learn about the path of σ_t at $t = -6$.

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

Figure 15: Macroprudential Policy Effects



Notes: The figure depicts aggregate lending (left column) and the percentage share of banks at the liquidation boundary (right column) during a simulated credit crisis (as given by Eq. (20)) and its aftermath under three macroprudential policies. Aggregate lending is shown as a percentage deviation relative to the preceding boom's peak, normalized at $t = 0$, and detrended using the steady-state growth rate. The top row presents the baseline case, where Ξ and α are constant 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 shows the outcome when the accounting rule α_t^{CCyB} is time-varying and relaxed after an adverse aggregate shock. The plot shows aggregate (fundamental) loans as solid lines, "low-shock" banks as dotted lines, and "high-shock" banks as dashed lines.

Ξ_t, thus, mirrors the path of σ_t.[50] 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 decreases relative to the baseline scenario, settling at a lower trend. This results

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

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. When the CCyB eases, banks with a high zombie loan ratio z opt to risk liquidation by increasing leverage. In sum, CCyB increases risk-taking behavior across the board, resulting in an initial increase in lending that is eventually offset by a larger number of bank failures. Contrary to the intended effects of the CCyB, the policy amplifies financial fragility.

The bottom row of Figure 15 presents the results of a policy that slows down the 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 4.34% to 2.34% at the peak of the crisis. The policy induces a much smoother lending series than the CCyB regime. Although relaxing accounting rules during credit risk events also induces more risk-taking than the benchmark, risk-taking is much lower than in the CCyB regime. This is because 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 easing up on loan loss recognitions postpones the deleveraging of high-shock banks. As a result, our findings suggest that relaxing loss recognition rules during periods with increased 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 receiving adverse shocks. The CCyB policy does not target the banks most needing a relaxation of capital rules or could relax the capital constraints for a bank just *before* it is hit 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 and better timed policy, creating better incentives for banks. Under delayed accounting, the bank cannot choose to lever up ex-ante; instead, it can increase its fundamental leverage only ex-post, in the dire 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 the 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. A regulatory reform designed to accelerate loss recognition induces a tradeoff between financial fragility and growth. Also, 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 bank dynamics and support regulatory design.

A limitation is that maintaining zombie loans does not cost resources and keeps inefficient firms alive. We also do not consider exogenous fluctuations in market values: forcing banks to recognize losses on marketable securities may induce excessive volatility if prices have non-fundamental components. Another limitation is that banks are treated in isolation in our model: in practice, banks have interconnected risk exposures and are subject to fire-sale externalities. Finally, we do not allow banks to choose how they adhere to accounting standards. Incorporating these features may further open important lines of research.

7 Data Availability Statement

The data underlying this article are available in Zenodo, at `https://doi.org/10.5281/zenodo.14565767`.

References

Abad, Jorge, Saki Bigio, Salomon Garcia-Villegas, Joel Marbet, and Galo Nuno, "The Heterogeneous Bank Lending Channel of Monetary Policy," Technical Report, Working Paper Bank of Spain 2024. 1

Acharya, Viral V and Anjan V Thakor, "The dark side of liquidity creation: Leverage and systemic risk," *Journal of Financial Intermediation*, 2016, *28*, 4–21. 34

Acharya, Viral V. and Stephen G. Ryan, "Banks' Financial Reporting and Financial System Stability," *Journal of Accounting Research*, May 2016, *54* (2). 9, A.2.2

Acharya, Viral V, Matteo Crosignani, Tim Eisert, and Christian Eufinger, "Zombie Credit and (Dis-) Inflation: Evidence from Europe," *The Journal of Finance*, 2024, *79* (3), 1883–1929. 12

_ **, Simone Lenzu, and Olivier Wang**, "Zombie lending and policy traps," Technical Report, National Bureau of Economic Research 2021. 12

Adrian, Tobias and Hyun Song Shin, "Liquidity and leverage," *Journal of financial intermediation*, 2010, *19* (3), 418–437. 16

_ **and** _ , "Procyclical leverage and value-at-risk," *The Review of Financial Studies*, 2013, *27* (2), 373–403. 4

_ **and Nina Boyarchenko**, "Intermediary Leverage Cycles and Financial Stability," 2013. New York Federal Reserve, Staff Report No. 567. 4, 1

—, Erkko Etula, and Tyler Muir, “Financial intermediaries and the cross-section of asset returns,” *The Journal of Finance*, 2014, *69* (6), 2557–2596. 4

Agarwal, Sumit, David Lucca, Amit Seru, and Francesco Trebbi, “Inconsistent regulators: Evidence from banking,” *The Quarterly Journal of Economics*, 2014, *129* (2), 889–938. 14

Atkeson, Andrew G, Adrien d’Avernas, Andrea L Eisfeldt, and Pierre-Olivier Weill, “Government Guarantees and the Valuation of American Banks,” in “NBER Macroeconomics Annual 2018, volume 33,” University of Chicago Press, 2018. 3.1

Basel Committee on Banking Supervision, “Basel III: A global regulatory framework for more resilient banks and banking systems,” Technical Report, Bank for International Settlements June 2011. A.2.1

Begenau, Juliane, “Capital requirements, risk choice, and liquidity provision in a business-cycle model,” *Journal of Financial Economics*, 2020, *136* (2), 355–378. 4, 1

— and Tim Landvoigt, “Financial regulation in a quantitative model of the modern banking system,” *The Review of Economic Studies*, 2022, *89* (4), 1748–1784. 4, 10

—, —, and Vadim Elenev, “Interest Rate Risk and Cross-Sectional Effects of Micro-Prudential Regulation,” *Available at SSRN*, 2024. 1

Behn, Markus, Rainer Haselmann, and Vikrant Vig, “The limits of model-based regulation,” *The Journal of Finance*, 2022, *77* (3), 1635–1684. 14

Benes, Jaromir and Michael Kumhof, “Risky bank lending and countercyclical capital buffers,” *Journal of Economic Dynamics and Control*, 2015, *58*, 58–80. 46

Bernanke, Ben and Mark Gertler, “Agency Costs, Net Worth and Business Fluctuations,” *The American Economic Review*, March 1989, *79* (1), 14–31. 7

Bernstein, Shai, Emanuele Colonnelli, Xavier Giroud, and Benjamin Iverson, “Bankruptcy spillovers,” *Journal of Financial Economics*, 2019, *133* (3), 608–633. 42

Bianchi, Javier and Saki Bigio, “Banks, liquidity management, and monetary policy,” *Econometrica*, 2022, *90* (1), 391–454. 1

Blank, Michael, Samuel G Hanson, Jeremy C Stein, and Aditya Vikram Sunderam, “How Should US Bank Regulators Respond to the COVID-19 Crisis?,” 2020. 13

Blattner, Laura, Luisa Farinha, and Francisca Rebelo, “When losses turn into loans: The cost of weak banks,” *American Economic Review*, 2023, *113* (6), 1600–1641. 11

Brunnermeier, Markus K. and Yuliy Sannikov, “A Macroeconomic Model with a Financial Sector,” *American Economic Review*, 2014, *104* (2), 379–421. 4, 1, 6, 8, 3.1, 5.1, C

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, “Fintech, regulatory arbitrage, and the rise of shadow banks,” *Journal of financial economics*, 2018, *130* (3), 453–483. 10

—, —, —, and —, “The secular decline of bank balance sheet lending,” Technical Report, National Bureau of Economic Research 2024. 10

Bushman, Robert M., "Transparency, Accounting Discretion, and Bank Stability," *FRBNY Economic Policy Review*, August 2016, pp. 129–149. 9, A.2.2

Caballero, Ricardo J., Takeo Hoshi, and Anil K. Kashyap, "Zombie Lending and Depressed Restructuring in Japan," *The American Economic Review*, 2008, *98* (5), 1943–1977. 11, 3.1

Chernenko, Sergey, Robert Ialenti, and David Scharfstein, "Bank Capital and the Growth of Private Credit," Technical Report, Harvard University Working Paper 2024. 10

Corbae, Dean and Pablo D'Erasmo, "Capital buffers in a quantitative model of banking industry dynamics," *Econometrica*, 2021. 4, 1, F.1

_ and Ross Levine, "Competition, stability, and efficiency in financial markets," in "Jackson Hole Symposium: Changing Market Structure and Implications for Monetary Policy, Kansas City Federal Reserve" 2018. 33

_ and _ , "Competition, Stability, and Efficiency in the Banking Industry," Technical Report, Working Paper, University of Wisconsin 2024. 1

DeMarzo, Peter M and Zhiguo He, "Leverage dynamics without commitment," *The Journal of Finance*, 2021, *76* (3), 1195–1250. 8

Diamond, Douglas W. and Philip H. Dybvig, "Bank Runs, Deposit Insurance, and Liquidity," *Journal of Political Economy*, 1983, *91*, 401–417. 3.1

Duffie, Darrell, *Measuring Corporate Default Risk*, Oxford University Press, 2022. 2

e Castro, Miguel Faria, "A quantitative analysis of the countercyclical capital buffer," 2021. 46

_ , Pascal Paul, and Juan M Sánchez, "Evergreening," *Journal of Financial Economics*, 2024, *153*, 103778. 12

Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh, "A macroeconomic model with financially constrained producers and intermediaries," *Econometrica*, 2021, *89* (3), 1361–1418. 1

Erel, Isil and Eduard Inozemtsev, "Evolution of debt financing toward less-regulated financial intermediaries in the united states," *Journal of Financial and Quantitative Analysis*, 2024, pp. 1–38. 10

Fama, Eugene F. and Kenneth R. French, "Common Risk Factors in the Returns on Stock and Bonds," *Journal of Financial Economics*, 1993, *33*, 131–156. 21

Federal Deposit Insurance Corporation, *Formal And Informal Enforcement Actions Manual* 2022. A.2.1

Flanagan, Thomas and Amiyatosh Purnanandam, "Why do banks hide losses?," *Available at SSRN 3329953*, 2019. 11, 3.1

Francis, Jennifer, J. Douglas Hanna, and Linda Vincent, "Causes and Effects of Discretionary Asset Write-Offs," *Journal of Accounting Research*, 1996. A.2.2

Gambacorta, Leonardo and Sudipto Karmakar, "Leverage and Risk-Weighted Capital Requirements," *International Journal of Central Banking*, December 2018, *14* (5), 153–191. 46

Gandhi, Priyank and Hanno Lustig, "Size anomalies in US bank stock returns," *The Journal of Finance*, 2015, *70* (2), 733–768. 2

Gertler, M., N. Kiyotaki, and A. Prestipino, "Chapter 16 - Wholesale Banking and Bank Runs in Macroeconomic Modeling of Financial Crises," in John B. Taylor and Harald Uhlig, eds., *Handbook of Macroeconomics*, Vol. 2, Elsevier, 2016, pp. 1345 – 1425. 6, 8

Gertler, Mark and Nobuhiro Kiyotaki, "Financial Intermediation and Credit Policy in Business Cycle Analysis," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3 of *Handbook of Monetary Economics*, Elsevier, 2010, pp. 547 – 599. 6

— **and** — , "Banking, liquidity, and bank runs in an infinite horizon economy," *American Economic Review*, 2015, *105* (7), 2011–2043. 6, 3.1

— **and Peter Karadi**, "A model of unconventional monetary policy," *Journal of Monetary Economics*, 2011, *58* (1), 17 – 34. ¡ce:title¿Carnegie-Rochester Conference Series on Public Policy: The Future of Central Banking April 16-17, 2010¡/ce:title¿. 6

— **, Nobuhiro Kiyotaki, and Albert Queralto**, "Financial crises, bank risk exposure and government financial policy," *Journal of Monetary Economics*, 2012, *59*, S17–S34. 6

Goh, Beng Wee, Dan Li, Jeffrey Ng, and Kevin Ow Yong, "Market pricing of banks' fair value assets reported under SFAS 157 since the 2008 financial crisis," *Journal of Accounting and Public Policy*, jan 2015. 52

Goldstein, Itay, Alexandr Kopytov, Lin Shen, and Haotian Xiang, "Bank heterogeneity and financial stability," *Journal of Financial Economics*, 2024, *162*, 103934. 1

Gomes, João, Urban Jermann, and Lukas Schmid, "Sticky Leverage," *American Economic Review*, 2016, *106* (12), 3800–3828. 8

Granja, João, "Bank Fragility and Reclassification of Securities into HTM," *University of Chicago, Becker Friedman Institute for Economics Working Paper*, 2023, (2023-53). 13

— **and Christian Leuz**, "The death of a regulator: strict supervision, bank lending, and business activity," Technical Report, National Bureau of Economic Research 2018. 14

Granja, Joao and Fabian Nagel, "Current Expected Credit Losses and Consumer Loans," *Available at SSRN 4324118*, 2023. 15

Hachem, Kinda and Zheng Song, "Liquidity rules and credit booms," *Journal of Political Economy*, 2021, *129* (10), 2721–2765. 10

Harris, Trevor, Urooj Khan, and Doron Nissim, "The Expected Rate of Credit Losses on Banks' Loan Portfolios," 2013. A.2.2

Hart, Oliver and John Moore, "A Theory of Debt Based on the Inalienability of Human Capital," *The Quarterly Journal of Economics*, 1994, *109* (4), pp. 841–879. 7

Haselmann, Rainer, Arkodipta Sarkar, Shikhar Singla, and Vikrant Vig, "The political economy of financial regulation," Technical Report, LawFin Working Paper 2022. 14

He, Zhiguo and Arvind Krishnamurthy, "A Model of Capital and Crises," *Review of Economic Studies*, 2012, *79(2)*, 735–777. 6

— **and** — , "Intermediary asset pricing," *The American Economic Review*, 2013, *103* (2), 732–770. 4, 1, 6, 3.1, 5.1, C

— **, Bryan Kelly, and Asaf Manela**, "Intermediary Asset Pricing: New Evidence From Many Asset Classes," *Journal of Financial Economics*, 2017, *126* (1), 1–35. 4, 16

Holmstrom, Bengt and Jean Tirole, "Financial Intermediation, Loanable funds, and the real sector," *Quarterly Journal of Economics*, 1997, *112* (3), 663–691. 7

Huizinga, Harry and Luc Laeven, "Bank valuation and accounting discretion during a financial crisis," *Journal of Financial Economics*, December 2012, *106* (3), 614–634. A.2.2

Jermann, Urban and Vincenzo Quadrini, "Macroeconomic Effects of Financial Shocks," *American Economic Review*, February 2012, *102* (1), 238–71. 1, 6

Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Monetary Tightening and US Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?," Technical Report, National Bureau of Economic Research 2023. 13

Kanzig, Diego R., "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements," *American Economic Review*, apr 2021, *111* (4), 1092–1125. B.1

Kelly, Bryan, Hanno Lustig, and Stijn Van Nieuwerburgh, "Too-systemic-to-fail: What option markets imply about sector-wide government guarantees," *American Economic Review*, 2016, *106* (6), 1278–1319. 3.1

Kilian, Lutz, "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market," *American Economic Review*, 2009, *99* (3), 1053–69. 2

Kisin, Roni and Asaf Manela, "The shadow cost of bank capital requirements," *The Review of Financial Studies*, 2016, *29* (7), 1780–1820. A.2.1

Kiyotaki, Nobuhiro and John Moore, "Credit Cycles," *Journal of Political Economy*, 1997, *105* (2), 211–248. 6

Kronmal, Richard A., "Spurious Correlation and the Fallacy of the Ratio Standard Revisited," *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 1993, *156* (3), 379–392. 18, 56

Laux, Christian and Christian Leuz, "Did fair-value accounting contribute to the financial crisis?," *The Journal of Economic Perspectives*, 2010, *24* (1), 93–118. 5, 13, A.2.2, 52

Leland, Hayne E. and Klaus Bjerre Toft, "Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads," *The Journal of Finance*, 1996, *51* (3), pp. 987–1019. 3.1

Milbradt, Konstantin, "Level 3 Assets: Booking Profits and Concealing Losses," *The Review of Financial Studies*, 2012, *25* (1), 55–95. 11

Nuño, Galo and Carlos Thomas, "Bank Leverage Cycles," *American Economic Journal: Macroeconomics*, April 2017, *9* (2), 32–72. 6

Peek, Joe and Eric S Rosengren, "Unnatural selection: Perverse incentives and the misallocation of credit in Japan," *American Economic Review*, 2005, *95* (4), 1144–1166. 11

Piazzesi, Monika, Ciaran Rogers, and Martin Schneider, "Money and banking in a New Keynesian model," *Standford WP*, 2022. 6

Plantin, Guillaume and Jean Tirole, "Marking to market versus taking to market," *American Economic Review*, August 2018, *108* (8), 2246–76. 13

Plosser, Matthew and Joao Santos, "Banks' incentives and inconsistent risk models," *The Review of Financial Studies*, 2018, *31* (6), 2080–2112. 11

Rios-Rull, Jose Victor, Tamon Takamura, and Yaz Terajima, "Banking Dynamics, Market Discipline and Capital," Feb 2023. 1

Shleifer, Andrei and Robert Vishny, "Fire Sales in Finance and Macroeconomics," *The Journal of Economic Perspectives*, 2011, *25* (1), pp. 29–48. 13

Simon, Luis, "Capital requirements in a model of bank runs: The 2008 run on repo," *Latin American Journal of Central Banking*, 2021, *2* (3), 100038. 46

Townsend, Robert, "Optimal Contracts and Competitive Markets with Costly State Verification," *Journal of Economic Theory*, 1979, *22*, 265–293. 7, 3.1, D.8

Vuolteenaho, Tuomo, "What drives firm-level stock returns?," *The Journal of Finance*, 2002, *57* (1), 233–264. 2