# Unintended Risks of Bank Capital Regulation

**Dongkeun Choi**[*]

University of California, San Diego

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**Abstract**

I show that tighter bank capital regulation can increase aggregate credit risk by shifting credit supply toward nonbank financial intermediaries (NBFIs) that operate outside the scope of regulation. Using U.S. mortgage data, I document that NBFIs approve observably similar applicants at higher rates than banks and that NBFI loans have higher default rates. I show that tighter bank capital regulation contributed to a shift in credit toward riskier borrowers with higher default rates. I develop a general equilibrium model in which banks and NBFIs choose loan rates and underwriting standards. In the model, tighter regulation leads banks to raise loan rates and tighten underwriting standards, shifting applicants toward NBFIs. NBFIs' looser underwriting standards extend credit to applicants who would otherwise remain unfunded, increasing aggregate credit risk. The model further shows that tighter regulation can amplify credit losses from adverse financial shocks.

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[*]University of California, San Diego, email: dochoi@ucsd.edu

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# 1. Introduction

Banks fund their lending activities through deposits and equity capital. To enhance the resilience of credit intermediation, capital regulations require banks to hold sufficient equity buffers relative to their assets to absorb unexpected losses and protect depositors.

However, recent empirical evidence identifies a channel through which capital regulation affects the economy by reshaping credit markets. Buchak et al. (2018) and Irani et al. (2021) document that capital regulations contributed to the rise of nonbank lenders in U.S. residential mortgage and syndicated corporate loan markets, respectively. The intuition is that when capital requirements constrain bank lending, credit supply can shift toward unregulated intermediaries, in particular, nonbank financial intermediaries (henceforth, NBFIs), which provide credit without taking deposits and operate outside the scope of bank capital regulation.

The expansion of NBFIs has prompted a discussion of the effectiveness of capital regulation when banks and NBFIs coexist.[1] Existing work has focused on balance-sheet responses to tighter capital requirements, such as the leverage of banks and NBFIs (Begenau and Landvoigt 2022) and banks' failure risk (Dempsey 2025). However, this leaves open how the migration of credit toward NBFIs affects the risk composition of aggregate credit. If NBFIs apply looser lending standards and originate riskier credit, tighter capital regulation does not simply reallocate credit across intermediaries but can also increase aggregate credit risk, undermining its original goal of maintaining the resilience of credit intermediation.

This paper shows that tighter bank capital regulation can *increase* aggregate credit risk when banks and NBFIs differ in lending standards, contributing to the literature in three ways. First, I show that loan approval decision is a key margin that generates differences between bank and NBFI loans. Using the U.S. residential mortgage loan-level data, I document that NBFIs are more likely than banks to approve applications conditional on applicant characteristics, particularly among riskier applicants. Second, I show that tighter regulation contributed to a shift toward riskier credit and higher subsequent defaults. Using regional variation in exposure to the Basel III capital requirement revisions, measured by the pre-Basel III period market share of regulated banks, I document that regions more exposed to the regulation experienced a credit shift toward riskier borrowers and higher subsequent default rates. Third, I develop a general equilibrium model consistent with the empirical findings and use it to conduct counterfactual analyses of the effectiveness of regulation under financial stress. The key innovation of the model is to allow

[1] General equilibrium analyses of capital requirements are extensive in settings where banks and NBFIs coexist, including Plantin (2015), Huang (2018), Ordonez (2018), Martinez-Miera and Repullo (2019), Donaldson et al. (2021), Farhi and Tirole (2021), Gebauer and Mazelis (2023), Darst et al. (2025), Lyonnet and Chretien (2025), and Xu (2025).

financial intermediaries to adjust their underwriting standards. Tighter bank capital requirements lead banks to increase loan rates and tighten underwriting standards to reduce expected credit losses. These changes shift marginal applicants toward NBFIs, resulting in applicants who would not be approved by banks receiving credit from NBFIs under their looser underwriting standards. This reallocation brings otherwise unfunded risk into the aggregate loan pool and increases aggregate credit risk. In addition, the model shows that tighter bank capital requirements can amplify aggregate credit losses during periods of financial stress.

I start by establishing empirical evidence on differences in lending behavior between banks and NBFIs using U.S. residential mortgage data. This setting is particularly well suited to this analysis because I can trace the lending process from application and approval to origination and subsequent performance, allowing me to identify at which stage differences between banks and NBFIs emerge. I use two main datasets. The first is Home Mortgage Disclosure Act (HMDA) data, which contain mortgage applications along with borrower and loan characteristics. I complement these data with loan-level performance data provided by Government-Sponsored Enterprises (GSEs) and Ginnie Mae, which allow me to track subsequent loan performance.

I first show that NBFI loans exhibit higher default rates than bank loans and that most of this gap reflects differences in the borrower risk composition of originated loans. Buchak et al. (2018) find a small default gap among GSE mortgages originated between 2010 and 2015 and limited differences in borrower characteristics. Bosshardt et al. (2025) document a wider default gap in 2016 and 2017 GSE loans and greater NBFI borrower risk when characteristics are considered jointly. I use a broader and longer-term sample than those used in prior studies, covering 2010 to 2024 and including Ginnie Mae loans. This broader coverage captures post-regulation differences between the two sectors more comprehensively, including stress periods. I find that NBFI loans exhibit default rates that are 2 percentage points higher than those of bank loans. I further show that 87 percent of the gap can be explained by differences in observable borrower risk.

I next show that approval decisions are a key margin generating the differences between bank and NBFI loans. I find that NBFIs are around 5 percentage points more likely to approve applications than banks, relative to an average approval rate of 79 percent, after controlling for observable borrower and loan characteristics. More importantly, the approval gap increases with applicant risk, as NBFIs become increasingly likely, relative to banks, to approve riskier applicants. I provide further evidence by comparing applicant pools before and after screening. Bank and NBFI applicant pools do not differ significantly in terms of borrower risk before screening. Among approved applications, however, the gap in observable risk widens, suggesting that differences in borrower risk emerge through the approval process.

As further corroboration, I document that tighter bank capital regulation contributes to a shift in the composition of newly originated mortgages toward riskier borrowers and higher subsequent default rates. Following Buchak et al. (2018) in exploiting regional heterogeneity, I use cross-regional variation in exposure to Basel III, which tightened bank capital regulation. I proxy regulatory exposure using the pre-Basel III market share of regulated banks. Using a difference-in-differences design across MSAs, I find a shift toward riskier newly originated credit in more exposed MSAs, reflected in both higher observable borrower risk and higher subsequent default rates. I further show that regulated banks exhibit lower approval rates following tighter capital regulation, while NBFI approval rates remain broadly unchanged. At the same time, the NBFI share of *applications* increases in more exposed regions. This indicates that the reallocation toward NBFIs operates through both a shift in applications and tighter bank lending standards.

I develop a model consistent with the empirical facts to study the effects of tighter bank capital regulation on aggregate credit risk in a counterfactual financial stress scenario when banks and NBFIs jointly supply credit. I build on the saver–borrower general equilibrium framework of Curdia and Woodford (2010) and Eggertsson et al. (2024) by allowing banks and NBFIs to supply credit and jointly choose loan rates and underwriting stringency. The most closely related theoretical framework is provided by Martinez-Miera and Repullo (2019). In their model, financial intermediaries choose screening effort, which affects project success. The capital held by a lender commits it to screen, and the intensity of screening determines loan risk. In my model, underwriting instead determines whether an application becomes a loan and whether the underlying credit risk can materialize. It also affects the volume of loan applications, since borrowers choose where to apply based on approval probabilities as well as loan rates.

In my model, banks and NBFIs differ along two institutional dimensions. The first is their funding structures. As Drechsler et al. (2017) show, banks obtain deposit funding at rates below the risk-free rate because they exercise market power in deposit markets. By contrast, NBFIs rely on money-market funding.[2] The second difference is regulatory exposure. Capital requirements apply only to banks and enter the model as an additional cost of lending, following Balloch and Koby (2023) and Buchak et al. (2024).

On the borrowing side, the representative borrower household consists of a continuum of members who face idiosyncratic application preferences that capture non-pricing factors (e.g., convenience and familiarity). After these preferences are realized, each member decides where to apply based on loan rates and approval probabilities, without knowing whether the application will

[2]I additionally introduce a reduced-form wedge that governs the extent to which each financial intermediary internalizes its default risk. This wedge captures differences arising from their funding sources and franchise values, highligthed by Kim et al. (2022). In the calibrated equilibrium, NBFIs internalize default risk less than banks, leading them to apply looser lending standards.

be approved.[3] In the calibrated equilibrium, banks offer lower loan rates but exhibit lower approval probabilities, whereas NBFIs offer higher loan rates but easier access to credit. Because neither offer dominates along both dimensions, each member chooses where to apply by considering both borrowing costs and approval probabilities against application preferences. Once applications are submitted to either sector, each intermediary evaluates its applicant pool according to its own underwriting policy, and rejected applicants fail to obtain credit.[4] At the repayment date, each borrower's creditworthiness and idiosyncratic repayment shock determine whether the loan defaults.

Tighter capital requirements create two opposing forces that affect aggregate credit risk. The first operates through banks. Higher capital requirements raise the marginal cost of bank lending, leading banks to increase loan rates. Higher loan rates increase not only the income banks receive when borrowers repay but also the losses banks face when borrowers default. Banks therefore have a stronger incentive to reduce default risk and tighten their lending standards. As a result, banks receive fewer applications and make fewer but safer loans. This reduces their contribution to the aggregate credit risk.

The second force operates through how applications are allocated across intermediaries. As capital requirements tighten, banks raise loan rates and lower approval probabilities, making bank loans less attractive. This leads some applicants who chose banks under the low-regulation regime to shift to NBFIs. Among these applicants, the key group is borrowers whose risk falls between the lending standards of the two sectors. Under the low-regulation regime, these borrowers applied to banks but were rejected. After tighter regulation, the bank offer becomes less attractive, so they shift to NBFIs and obtain credit because they satisfy the NBFI underwriting rule. As a result, risks that would otherwise remain unfunded enter the originated loan pool. This force raises not only the NBFI share of credit but also the aggregate credit risk.

I calibrate the model to match the credit allocation and performance of banks and NBFIs in the U.S. mortgage market. The calibrated model predicts that tighter capital regulation increases the aggregate default rate, implying that the increase in risk from the shift of applicants toward NBFIs is large enough to offset the reduction in risk from tighter bank underwriting. This result also holds when aggregate defaults are measured as defaulted principal, which takes into account changes in total credit. Although aggregate credit declines because NBFI loans do not fully substitute for

[3]In the baseline model, application friction shocks are independent of the creditworthiness of each member. Therefore, application volume responds to lenders' loan rates and approval probabilities, while the underlying distribution of borrower creditworthiness remains invariant. Section 6.2 relaxes this assumption.

[4]The borrowers are assumed to submit one application and not to reapply, as in DeFusco et al. (2020). Section 4.3.3 presents empirical evidence suggesting that reapplication is costly rather than frictionless. Section 6.2 shows that allowing costly reapplication weakens but does not overturn the main results.

bank loans, the decline in credit quality is large enough to outweigh this reduction in lending.

I then evaluate how the economy behaves after a financial stress event characterized by a decline in asset values, under different degrees of tightness in bank capital regulation. I subject the model to an exogenous shock that reduces the value of the loans held by both financial intermediaries. In this experiment, tighter bank capital requirements lead to a smaller erosion of bank equity and a faster recovery to the steady state. This is because, given the same size of the shock that deteriorates loan values, lower bank leverage under a tighter capital regulation regime translates into a smaller erosion of bank equity. However, banks cut lending more sharply after the shock under tighter capital regulation, and borrowers turn increasingly to NBFIs. Lending therefore shifts toward institutions with looser underwriting standards, raising cumulative credit losses. The larger credit losses also affect the real economy. The losses are borne by savers and reduce their consumption through the budget constraint. Borrowers' consumption also falls more in the higher-regulation regime as total lending declines further because NBFI lending cannot fully substitute for the cut in bank lending. Together, these consumption responses contribute to a larger decline in output under tighter bank capital regulation.

This unintended deterioration in credit outcomes under tighter bank capital regulation arises from differences in underwriting standards between banks and NBFIs in the first place. Tighter capital requirements lead banks to tighten underwriting, while NBFI standards remain unchanged, widening the gap between the two sectors. At the same time, more applicants shift to NBFIs, so more credit is evaluated under looser standards. These results suggest that tighter bank regulation should be accompanied by underwriting requirements for NBFIs. Under the counterfactual policy, NBFI underwriting standards become stricter as bank capital requirements tighten. The policy reduces the gap between the two sectors' lending standards and limits the increase in credit losses under the same financial stress scenario. Importantly, the complementary policy does not materially change the reduction in bank equity losses achieved by tighter bank capital regulation. The policy implication is that bank capital regulation should be complemented by a policy that directly reduces the underwriting gap between banks and NBFIs.

**Roadmap.** The remainder of the paper proceeds as follows. Section 2 documents differences between banks and NBFIs in mortgage applications, approval decisions, originated borrower risk, and subsequent loan performance, and examines how these differences changed following tighter bank capital regulation. Section 3 develops a static intermediary problem in which a financial intermediary jointly chooses its underwriting stringency and loan rate. Section 4 embeds banks and NBFIs in a general equilibrium framework with borrowers and savers. Section 5 calibrates the model to sector-level moments. Section 6 quantifies the effects of tighter bank capital requirements in steady state, and Section 7 quantifies them under financial stress. Section 8 evaluates a complementary minimum screening requirement for NBFIs. Section 9 briefly discusses why credit risk still matters even after securitization is taken into account, and Section 10 concludes.

# 2. NBFI Lending and Its Association with Capital Regulation

While credit intermediation has shifted from banks to NBFIs across both household and nonfinancial business credit markets in the U.S.,[5] this paper focuses on the residential mortgage market for two reasons. First, the data cover the credit creation process, from applications and approvals through subsequent performance and default, which allows me to identify at which stage banks' and NBFIs' loans exhibit differences. Second, they provide detailed information on borrowers and loan products as well as lender information.

**Data.** The main data consist of Home Mortgage Disclosure Act (HMDA) data and loan-level performance data from Fannie Mae, Freddie Mac, and Ginnie Mae. HMDA data cover roughly 90 percent of U.S. mortgage originations and are used to analyze the application stage, including approval and origination outcomes. The loan-level datasets from Fannie Mae, Freddie Mac, and Ginnie Mae cover roughly 65 percent of U.S. first-lien mortgage originations, provide monthly loan performance histories, and are used to analyze the relationship between borrower characteristics and ex post loan performance. The sample period runs from 2010 through 2024.

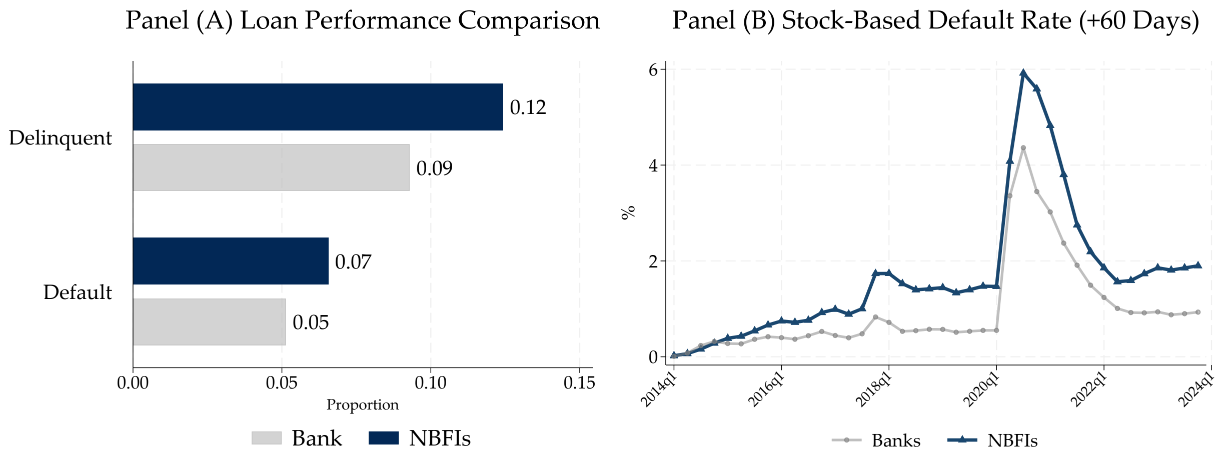
## 2.1. NBFI Loans Exhibit Higher Ex Post Default Rates

First, I examine whether loans originated by banks and NBFIs differ in terms of ex post performance. To compare ex post loan performance across originator types, I use loan-level performance data from Freddie Mac, Fannie Mae, and Ginnie Mae. These datasets track mortgage outcomes at a monthly frequency that allows me to construct measures of subsequent loan performance.

The two primary measures of ex post loan performance are the delinquency rate and the default rate. Following Agarwal et al. (2012), delinquency is defined as a loan becoming 30 or more days past due within two years of origination, while default is defined as a loan becoming 60 or more days past due within two years of origination. This measure is widely used in the literature, including Gerardi et al. (2018) and Adelino et al. (2019). Fuster and Willen (2017) further show that 80% of borrowers who are 60 days late on payments eventually enter foreclosure, suggesting that being 60 days delinquent is a strong sign of serious financial trouble.

[5] This shift extends beyond mortgage markets. In consumer credit, Fintech lenders and finance companies account for large shares of personal lending, with delinquency rates exceeding those of banks. In 2022, delinquency rates on unsecured personal loans were 1.89 percent for depository institutions, 3.38 percent for fintech lenders, and 7.01 percent for finance companies. In business credit, private credit, defined as debt provided by NBFIs to private businesses, has grown rapidly to a market comparable in size to leveraged loans and high-yield bonds.

**FIGURE 1.** Ex Post Loan Performance by Lender Type




**Notes.** Delinquency is defined as becoming 30 or more days past due within two years of origination, while default is defined as becoming 60 or more days past due within two years of origination (Agarwal et al. 2012). The left panel reports the average loan-level probability of default. The right panel reports monthly default rates by originator type for mortgages originated from 2014Q1 onward, tracking loan performance over time among loans observed in each month. The sample consists of loans sold to Freddie Mac, Fannie Mae, or placed into Ginnie Mae pools. *Sources.* Single-Family Loan-Level Datasets provided by Freddie Mac, Fannie Mae, and Ginnie Mae.

The left panel of Figure 1 shows that NBFI loans exhibit higher delinquency and default rates than bank loans on average. Specifically, the delinquency and default rates of NBFI loans are 3 and 2 percentage points higher, respectively, than those of bank loans. The right panel of Figure 1 reports calendar-time default rates. The default rate in this panel measures the share of loans that are 60 or more days past due among those that remain outstanding and are observed in the panel.[6] Because prepaid loans exit the performance panel, differences in prepayment between bank loans and NBFI loans can change the composition of loans observed over time. Nevertheless, the measure helps show when the performance gap between bank loans and NBFI loans becomes particularly large. Default rates rise gradually after 2014, increase sharply around 2020, and decline thereafter. The gap widens again during the policy rate hike period.

To assess whether the higher default rate of NBFI loans reflects differences in borrower composition or worse performance conditional on observed risk, I decompose the NBFI-bank default gap using a Blinder–Oaxaca decomposition (Blinder 1973; Oaxaca 1973). Details of the decomposition can be found in Appendix A.1. The decomposition indicates that borrower composition, differences in the risk distributions of the two sectors' loans, accounts for most of the NBFI-bank default gap. Differences in the underwriting risk distribution explain 86.8 percent of the gap, while the conditional-performance component accounts for the remaining 13.2 percent. This suggests that

[6] The panel starts in 2014 because Ginnie Mae loan-level performance data are available beginning in 2014.

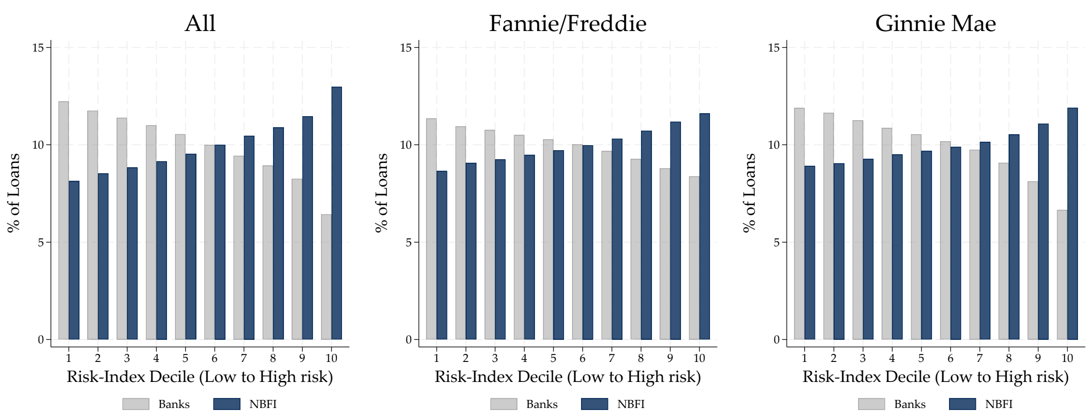
NBFI loans do not perform substantially worse than bank loans once observed risk is controlled for, which is consistent with Fuster et al. (2019).

## 2.2. NBFI Loans Have Riskier Observable Profiles

In this section, I provide direct evidence by comparing the distributions of observable risk of the loans originated by each type of lender. Previous evidence on differences in observable risk between bank and NBFI loans is mixed. Fuster et al. (2019) compare banks and NBFIs using HMDA data and report that NBFIs originate loans to borrowers with lower income and higher loan-to-income ratios than banks. Buchak et al. (2018) use Fannie Mae and Freddie Mac conforming loans and find that NBFI borrowers have slightly lower FICO scores and higher debt-to-income (DTI) ratios, but also lower loan-to-value (LTV) ratios. Examining each characteristic separately is informative, but it may miss differences in borrowers' overall underwriting profiles.

I construct a risk index measure for borrowers' observable risk as the first principal component of credit score, LTV ratios, and DTI ratios.[7] Then, I compare the distribution of originated loans across risk levels between banks and NBFIs.

**Figure 2.** Share of Lending by Risk Decile Within Banks and NBFIs




**Notes.** The risk index is constructed using principal component analysis of credit scores, DTI, and LTV, and is normalized so that higher values correspond to riskier underwriting profiles. Loans are sorted into deciles of the risk index. The figure shows the distribution of originated loans across risk-index deciles, separately for banks and NBFIs. The shares are computed within lender type. Each title represents the loans used to construct the figure. *Sources.* Single-Family Loan-Level Datasets provided by Freddie Mac, Fannie Mae, and Ginnie Mae, and author's calculations.

Figure 2 reports the distribution of originated loans across risk-index deciles, separately for banks and NBFIs. The first panel shows the results using the full sample, while the remaining two

[7] Bosshardt et al. (2025) regress a default indicator on bins of credit scores, LTV ratios, and DTI ratios and construct their risk index using the fitted values. In contrast, I use principal component analysis to construct an index directly from the joint variation in these underwriting characteristics without relying on ex post loan outcomes.

panels report results separately for GSEs (Freddie Mac and Fannie Mae) and Ginnie Mae loans. Bank loans are more concentrated in lower-risk deciles, whereas NBFI loans are more concentrated in higher-risk deciles. As the risk decile increases, the share of bank loans declines steadily, while the share of NBFI loans rises. This divergence is not readily apparent from a comparison of average borrower characteristics. It shows that NBFIs originate relatively more loans to borrowers with lower credit scores, higher DTI ratios, and higher LTV ratios. As the rest of the panels show, the main results are not driven by Ginnie Mae loans, which target low-income applicants.

To connect with the literature that examines individual underwriting characteristics separately across lender types, Appendix A.2 reports univariate comparisons of credit scores, DTI ratios, and LTV ratios. These distributional comparisons show that NBFI loans are more concentrated among borrowers with lower credit scores, higher DTI ratios, and higher LTV ratios.

## 2.3. NBFIs Approve Applications at Higher Rates

A natural next question is at which stage the riskier composition of NBFI loans emerges. One possibility is that NBFIs are more likely to approve an application than banks conditional on observable borrower and loan characteristics. Another is that NBFIs attract a riskier pool of applicants *before* approval decisions are made. If the difference arises at the approval stage, lenders' underwriting decisions are key margins. If it is already present in the applicant pool, however, borrowers' sorting matters for understanding how credit risk is realized in the economy.

### 2.3.1. Approval Rate Gap between Banks and NBFIs

To first quantify differences in approval propensities, I estimate an application-level linear probability model in which an approval indicator is regressed on lender type and application characteristics, using HMDA data.[8] The estimated regression model is

$$\mathbb{I}\left(Approved_{l,t}\right) = \beta \cdot \mathbb{I}\left(NBFI_l\right) + \Gamma' X_{l,t} + \alpha_{c,t} + \varepsilon_{l,t}, \tag{1}$$

where $\mathbb{I}[Approved_{l,t}]$ equals one if application $l$ in year $t$ is approved,[9] and $\mathbb{I}[NBFI_l]$ equals one if the lender processing the application is an NBFI. The coefficient of interest is $\beta$, which measures the NBFI approval differential relative to banks after conditioning on observables. The vector $X_{l,t}$

[8] Most mortgage borrowers in the U.S. submit only one application, according to Consumer Financial Protection Bureau (2015) and Bhutta et al. (2026). In addtion, the given regression captures how banks and NBFIs exhibit different propensities to approve applications given the applicants' observable characteristics. Whether a given household eventually obtains a loan is another margin that this regression does not estimate.

[9] An application enters the approval denominator when the HMDA action taken code equals 1, 2, or 3, where 1 denotes a loan originated, 2 denotes an application approved but not accepted by the applicant, and 3 denotes an application denied. The approval indicator equals one when the action taken code is 1 or 2.

includes LTV, DTI, income, loan amount, loan purpose, and applicant demographic characteristics, including gender, ethnicity, and age.[10] County-by-year fixed effects $\alpha_{c,t}$ absorb local demand conditions common to lenders operating in the same county and year. I separately define high-risk applications as those with DTI ratios of at least 45 percent and LTV ratios of at least 70 percent to examine whether approval rates differ across lender types within the higher-risk applicant pool.[11]

**Table 1.** NBFIs Exhibit Higher Approval Rates

| | Conforming | | | | | | All | |
|---|---|---|---|---|---|---|---|---|
| | Conventional | | FHA | | All | | | |
| | (1) Full | (2) High-Risk | (3) Full | (4) High-Risk | (5) Full | (6) High-Risk | (7) Full | (8) High-Risk |
| $\mathbb{I}[NBFI]$ | **0.049**$^{***}$ | **0.067**$^{***}$ | **0.035**$^{***}$ | **0.055**$^{***}$ | **0.038**$^{***}$ | **0.114**$^{***}$ | **0.048**$^{***}$ | **0.081**$^{***}$ |
| | (0.009) | (0.011) | (0.009) | (0.010) | (0.009) | (0.012) | (0.009) | (0.011) |
| Log Loan-to-Value | -0.024$^{***}$ | -0.264$^{***}$ | 0.034$^{**}$ | -0.194$^{***}$ | -0.037$^{***}$ | -0.091$^{***}$ | -0.029$^{***}$ | -0.261$^{***}$ |
| | (0.003) | (0.036) | (0.017) | (0.065) | (0.005) | (0.021) | (0.004) | (0.033) |
| Log Debt-to-Income | -0.227$^{***}$ | -2.685$^{***}$ | -0.117$^{***}$ | -1.099$^{***}$ | -0.210$^{***}$ | -1.706$^{***}$ | -0.213$^{***}$ | -1.928$^{***}$ |
| | (0.009) | (0.031) | (0.011) | (0.026) | (0.008) | (0.034) | (0.009) | (0.033) |
| Log Income | 0.027$^{***}$ | 0.031$^{***}$ | 0.071$^{***}$ | 0.118$^{***}$ | 0.037$^{***}$ | 0.074$^{***}$ | 0.027$^{***}$ | 0.070$^{***}$ |
| | (0.003) | (0.004) | (0.012) | (0.014) | (0.003) | (0.005) | (0.003) | (0.005) |
| Average Approval Rate | 0.781 | 0.526 | 0.791 | 0.781 | 0.789 | 0.670 | 0.791 | 0.669 |
| Fixed Effect | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 30,758,023 | 3,567,007 | 5,122,992 | 2,359,968 | 38,645,573 | 6,792,373 | 40,533,494 | 6,989,249 |
| Adj. R-squared | 0.160 | 0.495 | 0.130 | 0.177 | 0.144 | 0.328 | 0.141 | 0.351 |

**Notes.** Standard errors are two-way clustered at the county and lender levels and are reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. Columns (1)–(6) restrict the sample to conforming loans, split into conventional loans, FHA loans, and all loan types pooled. Columns (7)–(8) use all loans without the conforming restriction. Full refers to all applications. High-Risk refers to applications with DTI≥ 45 and LTV≥ 70. Fixed Effect captures loan purpose, applicant demographic characteristics (gender, ethnicity, age), and county×year. *Sources.* HMDA and author's calculations.

Table 1 shows that NBFIs approve observably comparable applications at higher rates than banks. In the conventional conforming sample, which is reported in columns (1) and (2), NBFI applications are 4.9 percentage points more likely to be approved than otherwise similar bank applications. The approval gap increases to 6.7 percentage points in the high-risk subsample. This suggests that even in segments of the mortgage market subject to secondary-market purchase rules, NBFIs exhibit higher approval rates than banks. For FHA loans, shown in columns (3) and (4), the corresponding gaps are 3.5 and 5.5 percentage points. When FHA and other government-insured loans are included in the conforming sample, reported in columns (5) and (6), the gap is 3.8 percentage points in the full sample and rises to 11.4 percentage points among high-risk

[10]One concern is that HMDA does not report credit scores. However, if NBFI applicants have lower credit scores than bank applicants conditional on the included observables, omitting credit scores would bias the estimated approval gap downward because lower credit scores reduce approval probabilities.

[11]DTI and LTV capture two important dimensions of mortgage credit risk, repayment capacity and borrower leverage, both of which are closely related to mortgage default risk. The 45 percent DTI cutoff also corresponds to a salient threshold in GSE underwriting guidelines.

applicants. The pattern remains when jumbo loans are also included, with approval gaps of 4.8 and 8.1 percentage points in the full and high-risk samples, reported in columns (7) and (8), respectively.

### 2.3.2. Observable Applicant Composition and Approval Stage Divergence

Beyond NBFIs' higher approval propensity, their originated loans may appear riskier simply because riskier borrowers are more likely to apply to NBFIs in the first place. To examine this margin, I use the same HMDA data as in the approval analysis and compare the observable characteristics of applicants across lender types *before* approval decisions are made. Observable applicant risk is summarized using principal component analysis, following the same approach used for originated loans. The index is based on income, DTI, and loan amount, and is normalized so that higher values indicate riskier applicant profiles. I standardize the index using the full sample of bank and NBFI applications, including both approvals and rejections.[12]

I test whether applicant pools differ statistically after accounting for geography, loan type, and time. For each applicant risk proxy, I estimate

$$Proxy_{l,c,t} = \beta \times \mathbb{I}[\text{NBFI}_l] + \alpha_{c,t} + \varepsilon_{l,c,t}, \tag{2}$$

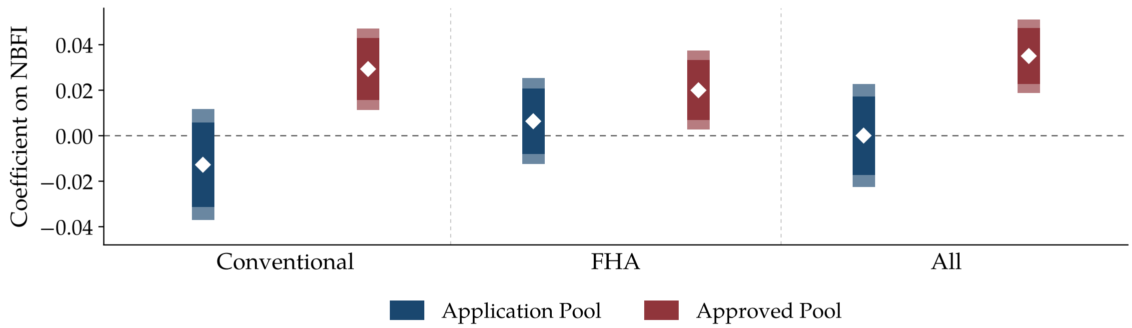
where $Proxy_{l,c,t}$ denotes the applicant risk proxy for application $l$ in county $c$ and year $t$. $\mathbb{I}[\text{NBFI}_l]$ equals one for applications submitted to NBFIs and zero for applications submitted to banks. The specification absorbs county-by-year fixed effects and standard errors are clustered at the county level. The coefficient $\beta$ measures whether applicants to NBFIs differ systematically from applicants to banks along observable risk, conditional on these controls.

Figure 3 plots the estimated coefficient on $\mathbb{I}[\text{NBFI}_l]$ across market segments, including conventional loans, FHA loans, and the full market. At the application stage, which includes both approved and rejected applications, the estimated NBFI-bank difference in applicant risk is close to zero. By contrast, among *approved* applications, the difference shifts toward higher risk for NBFIs. This pattern suggests that the risk gap emerges at the approval stage rather than from observable sorting in the applicant pool.

**Robustness Checks.** Regarding the approval propensity gap, the evidence shows that approval behavior is particularly important among riskier applicant pools and contributes to the riskier composition of NBFI loans. To examine this pattern more closely, Appendix B.1 shows that the NBFI approval gap increases across deciles of observable risk and is largest among riskier applicants.

[12]While the measure omits credit scores because HMDA does not report them, I merge the HMDA data with GSE loan performance data following Buchak and Jørring (2026) and show that the measure aligns closely with credit scores. See Figure 6, which shows the relationship between the negative of the riskiness index, referred to as creditworthiness, and credit score.

**Figure 3.** Differences in Applicant Risk by Lender Type




**Notes.** The figure reports the coefficient on the NBFI indicator from regressions of the applicant risk proxy on the NBFI indicator. Blue estimates are based on all applications, while red estimates are based on approved applications. Vertical bars indicate confidence intervals, with darker and lighter shades corresponding to the 95% and 99% confidence intervals, respectively. All regressions absorb county-by-year fixed effects, and standard errors are clustered at the county level. *Sources.* HMDA and author's calculations.

Regarding the distribution of applicant risk, I examine the distribution of the applicant risk proxy by lender type and year across mortgage market segments in Appendix B.2. The distribution of NBFI applicants largely overlaps with that of bank applicants, indicating that NBFI applicants do not appear observably riskier than bank applicants at the application stage.

## 2.4. Capital Requirements and NBFIs' Lending

The preceding sections show that NBFIs extend credit to riskier borrowers under more lenient underwriting standards and that their loans subsequently perform worse. Prior work by Buchak et al. (2018) and Irani et al. (2021) shows that tighter bank capital regulation contributed to the growth of NBFI lending. This raises a natural question of whether the expansion of NBFI lending following tighter capital regulation merely changes who supplies credit or also changes the credit risk of borrowers receiving loans and the subsequent performance of those loans.

### 2.4.1. Capital Regulation Contributed to Higher Borrower Risk and Default Rates

I examine whether tighter capital regulation affects borrower risk and subsequent default rates, building on Buchak et al. (2018) by exploiting regional variation in exposure to the Basel III capital reform, which tightened banks' capital requirements. In particular, I estimate dynamic difference-in-differences specifications comparing MSAs with greater and lesser exposure.

**Regulation Exposure Measure.** To measure local exposure to the U.S. Basel III capital reform, I define $\mathbb{I}[\text{Regulated}_b]$ as an indicator equal to one if financial intermediary $b$ was subject to the Basel III capital requirements announced by the U.S. banking agencies on June 7, 2012, and zero otherwise. I aggregate this indicator using each intermediary's pre-reform mortgage market share within an MSA. Let $s_{mb,2008}$ denote intermediary $b$'s share of mortgage originations in MSA $m$ in 2008.[13] I define MSA-level regulatory exposure as

$$\text{Regulation}_m = \sum_{b \in \mathcal{B}} s_{mb,2008} \times \mathbb{I}[\text{Regulated}_b]. \tag{3}$$

Thus, $\text{Regulation}_m$ is the share of mortgage originations in MSA $m$ in 2008 accounted for by banks classified as exposed to the tighter capital requirements and captures cross-sectional variation in local mortgage markets' pre-Basel III reliance on these banks. The mean of $\text{Regulation}_m$ is 0.42, with a standard deviation of 0.12, and the interquartile range is 0.18.

**Difference-in-Differences Specification.** I estimate the following event-study specification

$$Y_{m,t} = \sum_{\tau=2010Q1, \tau \neq 2012Q2}^{2019Q4} \beta_\tau \times \mathbb{I}[t = \tau] \times \text{Regulation}_m + \mathbf{X}'_{m,t}\Gamma + \alpha_m + \delta_t + \varepsilon_{m,t}, \tag{4}$$

The dependent variable $Y_{m,t}$ is measured at the MSA-quarter level and includes the NBFI market share, the average borrower credit score, and the default rate. I construct these measures using GSE data for newly originated loans containing information on borrower characteristics, loan amounts, and subsequent loan performance.

The NBFI market share is defined as the share of GSE loans originated by NBFIs in MSA $m$ during quarter $t$. For borrowers' creditworthiness, I calculate the average credit score of loans originated in MSA $m$ at time $t$. For robustness checks, I also utilize the borrower risk index, which I construct using the first principal component of credit score, DTI, and LTV, as in Section 2.2. Finally, the default rate is measured based on newly originated loans. Specifically, for loans originated in MSA $m$ during time $t$, I calculate the share of loans that default, where default is defined as in Section 2.1.[14]

The specification includes MSA fixed effects, $\alpha_m$, to absorb differences across local mortgage markets, and quarter fixed effects, $\delta_t$, which control for aggregate macroeconomic shocks common to all regions. The identifying assumption is that, conditional on the controls, MSAs with different pre-Basel III exposure would have followed similar outcome trends in the absence of the regulatory change. The vector $\mathbf{X}_{mt}$ includes pre-Basel III local market characteristics interacted with quarter indicators, which addresses the concern that regulatory exposure may be correlated with banks'

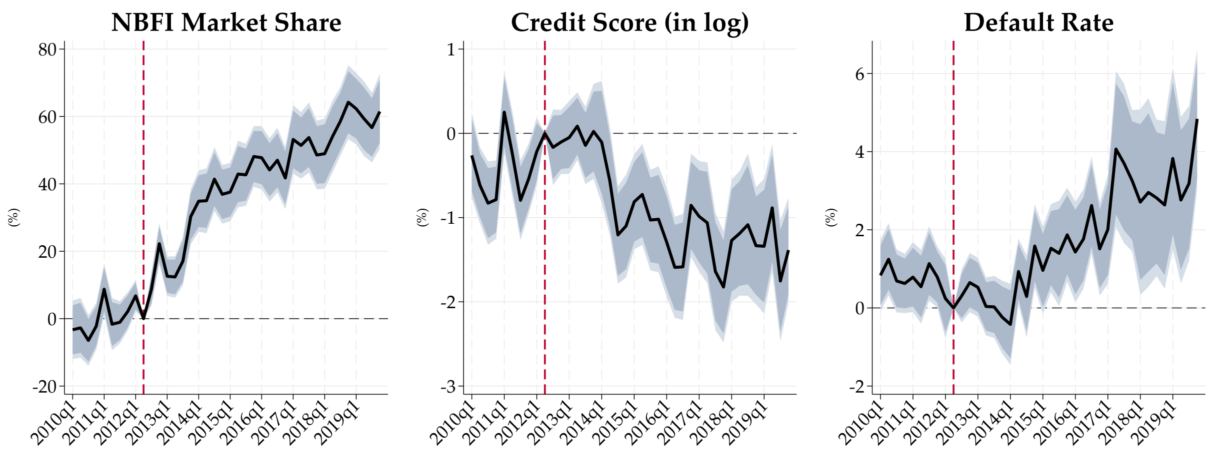
[13] I use 2008 market shares following Buchak et al. (2018), which mitigates concerns about anticipation effects. Discussions of tighter capital regulation began around 2010, and the Basel III capital rules were formally proposed in June 2012. Market shares measured closer to these dates may therefore already reflect lenders' responses to the anticipated regulatory changes.

[14] The default rate reflects the subsequent performance of each quarter's newly originated loans rather than the performance of the outstanding loans at time $t$.

geographic sorting and local housing market dynamics. To account for differences in fintech demand across regions, as highlighted by Fuster et al. (2019), I control for the share of the population aged 18 to 44 as a proxy for the use of fintech channels. $\mathbf{X}_{mt}$ includes house price growth during the 2004–2007 boom, the homeownership rate, density, the unemployment rate, and the share of the population aged 18–44, each interacted with time indicators.[15]

The omitted period is 2012Q2, as the proposed rules were announced on June 7, 2012. Given the time between application, lending decisions, and recorded originations, loans appearing in the data in 2012Q2 largely reflect applications and lending decisions made before the announcement.

**Figure 4. Dynamic Effects of Bank Regulation on NBFI Share in Origination, Borrowers' Riskiness, and Defaults**




**Note.** This figure reports the event-study estimates $\{\beta_\tau\}$ from equation (4), where MSA-level regulatory exposure, $Regulation_m$, is interacted with quarter indicators. The omitted period is 2012Q2. The dependent variables are NBFI mortgage market share, the average credit score in logarithm, and the mortgage default rate. The specification includes MSA fixed effects, quarter fixed effects, and pre-Basel III local characteristics interacted with quarter indicators. The solid lines represent the point estimates, and the shaded areas denote 90 and 95 percent confidence bands clustered at the MSA level. *Sources:* HMDA, Single-Family Loan-Level Datasets provided by Freddie Mac and Fannie Mae

**Estimation Results.** The first panel of Figure 4 shows the effects of regulatory exposure on NBFI market share. MSAs with greater exposure to regulated banks experience an increase in the NBFI share of origination, which is consistent with the finding of Buchak et al. (2018).

The novel findings are based on the borrower risk index and subsequent default rates. The second panel of Figure 4 reports the estimated coefficients on the borrower risk proxied by average credit score. The results show that regions with greater exposure to the regulation experienced a credit shift toward riskier borrowers. The coefficients remain close to zero in the immediate

[15] I examine whether regions with greater regulatory exposure systematically differ in these pre-regulation characteristics. Appendix C.1 reports the standardized differences across the two groups.

post-announcement period and become persistently positive around 2014. Thus, the increase in the NBFI origination share precedes the persistent deterioration in observable borrower risk.

The default rate estimates provide additional consistent evidence. As shown in the third panel of Figure 4, the estimated coefficients begin to rise around 2014 and become more pronounced. This timing coincides with the persistent increase in borrower risk, suggesting that the deterioration in realized loan performance is associated with the shift toward riskier borrowers.

**Robustness Checks** I conduct robustness checks by excluding all covariates, as suggested in Altonji et al. (2005) and Oster (2019). Second, I address a concern that regulated banks may also have been involved in significant legal disputes and that other mortgage-related assets, such as mortgage servicing rights, may be an important channel driving the results. To address these concerns, I additionally control for regional-level Legal Issue/Asset and MSR/Equity measures, each constructed as the market-share-weighted average of the corresponding bank-level ratio using mortgage market shares as weights.[16] The results are robust to changes in the covariates.

In addition, I estimate the responses of the average borrower risk index, which includes not only credit score but also LTV and DTI, and the amount of defaulted principal. I show that the average borrower risk index rises in regions with greater exposure to the regulation and that defaulted principal in those regions also increases after the regulation. Results are reported in Appendix C.2.

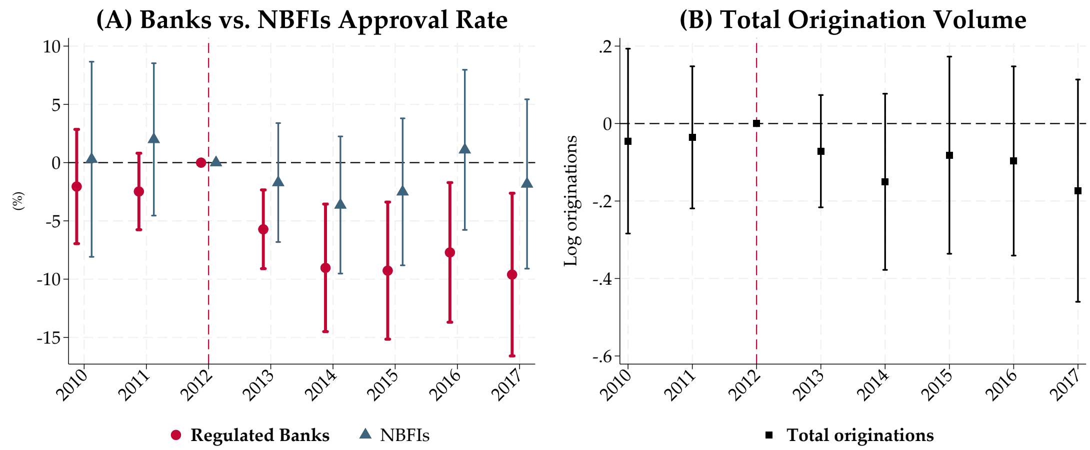
### 2.4.2. Tighter Capital Regulation Contributed to a Decline in Bank Approval Rates

I next examine whether regulatory exposure affected the approval decisions of regulated banks and NBFIs differently. Furthermore, I test whether regulatory exposure affected the total amount of loans originated in a given region. To do so, I reestimate the same empirical specification using HMDA data and examine approval rates separately for regulated banks and NBFIs.

Figure 5 reports the results. Panel (A) shows that the approval rate of regulated banks declines by approximately 10 percentage points as regulatory exposure increases from zero to one. In contrast, the approval rate of NBFIs does not exhibit statistically significant changes. These results show that regulated banks tightened their lending standards, reflected in lower approval rates, whereas NBFIs maintained their approval rates. For robustness checks, I calculate the residual of each application approval decision after controlling for borrower characteristics, including income, loan size, purpose, sex, and ethnicity, and recompute the response using the average residual approval rate. This residualized measure isolates changes in lending standards from changes in the

[16] I compile major mortgage-related settlements and enforcement actions reported in public DOJ, Federal Reserve, OCC, HUD, SEC, and FHFA documents during 2010–2012, assign each event to the ultimate parent bank, and aggregate the publicly reported dollar amounts through 2012.

**Figure 5. Dynamic Effects of Regulation on Approval Rates and Total Credit**




**Note.** This figure reports the annual event-study estimates $\{\beta_\tau\}$ from equation (4), where MSA-level regulatory exposure, $Regulation_m$, is interacted with year indicators. The omitted year is 2012. In Panel (A), the dependent variables are the approval rates of banks and NBFIs within each MSA. In Panel (B), the dependent variable is the MSA-level total credit originated. The specification includes MSA fixed effects, year fixed effects, and pre-Basel III local characteristics interacted with year indicators. Vertical bars denote 95% confidence intervals based on standard errors clustered at the MSA level. *Source.* HMDA

observable composition of applicants. The results are robust and are presented in Appendix C.3.

Then, I examine the total amount of loans originated in a given region. Panel (B) shows that regions with greater exposure to this regulation experienced a decrease in total loan supply, although the decrease lacks statistical significance.

Finally, I test the response of the NBFI *application* share and find that it also rises after the regulation. Regions with greater exposure to the regulation exhibit faster growth in the NBFI application share, although the increase is smaller than that in the NBFI origination share. This difference can be partly explained by the widening approval-rate gap between the two sectors. The results are reported in Appendix C.3.

# 3. A Static Financial Intermediary Problem

I develop a general equilibrium model consistent with the empirical facts to examine how tighter bank capital requirements affect aggregate credit risk under financial stress scenarios. In the model, both banks and NBFIs supply credit within a saver-borrower framework.

In this section, I first provide a static intermediary problem in which the intermediary jointly chooses the loan rate and underwriting stringency, which determine which borrowers can obtain loans. This problem is later embedded in the problems of banks and NBFIs in the full model. I use this problem to show the channel through which capital regulation affects banks' underwriting standards. The model differs from Martinez-Miera and Repullo (2019), where costly effort directly changes borrowers' default probabilities. In my model, underwriting instead changes which borrowers are approved and the risk composition of originated loans.

## 3.1. Timing and Setup

Time is discrete, and each intermediary $i$ operates under monopolistic competition, taking the loan rates posted by other lenders as given. The intermediary originates one-period nominal loans and finances them with external funding at the gross rate $R^f$.[17]

At the beginning of period $t$, the intermediary jointly sets the loan rate $R^L$ and its underwriting stringency $q$ to maximize its profit. $q$ determines which borrowers, based on observables, can be approved and determines the approval probability $p(q)$. Applicants observe the approval probability before submitting an application, but do not directly observe $q$ or know whether their application will be approved. Instead, they choose where to apply based on the loan rate and the observed approval probability. Once applications are submitted to each lender, the lender decides which applicants receive loans based on the underwriting stringency $q$ and the distribution of applicants' creditworthiness. Approved applicants receive loans at date $t$, and idiosyncratic repayment shocks determine default on these loans at date $t + 1$.

The stringency $q$ shapes the intermediary's profit through three distinct channels. The first channel through which $q$ affects profit is origination volume. $q$ can be interpreted as a cutoff on applicants' observable creditworthiness. A higher $q$ requires higher creditworthiness and lowers the approval probability, implying $p'(q) < 0$. Because applicants can only observe the approval probability, not $q$ itself, stricter underwriting also reduces application demand, $L^{app}(R^L, p(q))$, by making the offer less attractive to applicants. Details are discussed in Section 4.3, which presents the borrower's problem. The resulting volume of originated loans $L^{orig}(R^L, q)$ is

$$L^{orig}(R^L, q) = p(q) \cdot L^{app}(R^L, p(q)).$$

The second channel is through underwriting costs. To maintain underwriting stringency $q$, the intermediary needs to pay a cost of $s(q)$ per dollar of originated lending, with $s'(q) > 0$.

The third channel operates through default. On the repayment date, idiosyncratic repayment

[17] Although the empirical facts are based on residential mortgages, I model loans as one-period claims. This interpretation matches the empirical default measure, which tracks subsequent delinquency among newly originated mortgages. A natural extension that separates new originations from outstanding stocks can be done by incorporating the settings in Garriga et al. (2017) and Berger et al. (2021). This extension allows each intermediary to have a flow of newly originated loans, an outstanding principal stock, a promised payment stock, and a risk stock embedded in the outstanding pool. The *stock* default rate then evolves as new originations with current default risk are added to inherited stocks.

shocks are realized for borrowers with approved loans. Borrowers with higher creditworthiness have greater repayment capacity and are therefore less likely to fall below the default threshold. Under underwriting stringency $q$, the default rate among approved loans can be summarized by $d(q)$. A higher $q$ shifts the composition of approved loans toward safer borrowers, which lowers the expected default rate among originated loans and implies $d'(q) < 0$. Details of the default incidence and the underlying assumptions are provided in Section 4.3.

Each dollar of originated lending requires one dollar of external funding at a cost of $R^f$, and therefore the intermediary faces the funding requirement $F = L^{orig}(R^L, q)$. The intermediary's profit can therefore be written as

$$\Pi(R^L, q) = \Big[ (1 - d(q))\, R^L - s(q) - R^f \Big] \cdot p(q) \cdot L^{app}(R^L, p(q)). \tag{5}$$

The first term is the revenue per dollar of lending. A fraction $d(q)$ of originated loans defaults, so the intermediary collects $(1 - d(q))R^L$ per dollar of originated lending.[18] The intermediary also pays the underwriting cost $s(q)$ and the funding cost $R^f$ for each dollar originated. Multiplying the resulting per-dollar margin by $p(q)L^{app}(R^L, p(q))$ gives total profit.

## 3.2. First Order Conditions

Given that application demand is differentiable in the loan rate and has a constant loan-rate elasticity $\varepsilon > 1$, the first-order condition with respect to $R^L$ implies

$$R^L = \frac{\varepsilon}{\varepsilon - 1} \frac{1}{1 - d(q)} (R^f + s(q)). \tag{6}$$

The intermediary applies the markup factor $\varepsilon/(\varepsilon - 1)$ to the per-dollar marginal cost of origination, $R^f + s(q)$, adjusted by the expected repayment share $1 - d(q)$.

The first-order condition with respect to $q$ can be derived as

$$\underbrace{-d'(q)R^L}_{\text{default-risk margin}} = \underbrace{s'(q)}_{\text{underwriting-cost margin}} \underbrace{- \Big((1 - d(q))R^L - R^f - s(q)\Big) \left(\frac{p'(q)}{p(q)} + \frac{d \log L^{app}(R^L, p(q))}{dq}\right)}_{\text{volume margin}}. \tag{7}$$

The left-hand side of equation (7) captures the marginal benefit of tightening underwriting stringency. Raising $q$ lowers the default probability at the marginal rate $-d'(q)$, so the resulting reduction in expected default losses is $-d'(q)R^L$. The right-hand side captures the costs of tighten-

[18]In this setting, the financial intermediary bears the full losses from defaults on the loans it originates. This assumption is discussed in Section 3.4 and relaxed in the general equilibrium model.

ing underwriting stringency. The first term denotes the direct cost of operating under a stricter underwriting standard. The second term captures the margin lost from originating fewer loans as both the approval rate and application demand decline. The term $p'(q)/p(q)$ captures the change in approval rate, while $d \log L^{app}(R^L, p(q))/dq$ captures the change in application demand.

## 3.3. Complementarity between Loan Rates and Underwriting Stringency

In this section, I show how an increase in the cost of funding $R^f$ changes both the underwriting standard and the loan rate. The reason is because, once the financial intermediary problem is extended to a bank problem, the capital requirement is introduced as an additional cost that the bank needs to internalize when maximizing profits. The proposition below therefore provides a channel through which capital requirements affect banks' choices.

Proposition 1. *Suppose $s'(q) > 0$ and the interior optimum satisfies the second-order condition. Then*

$$\frac{dq^*(R^f)}{dR^f} > 0.$$

Proof. See Appendix D.1. □

The mechanism is a complementarity between the loan rate and underwriting. A higher funding cost $R^f$ raises the posted loan rate through equation (6). Using the envelope condition, a higher loan rate increases the amount the intermediary loses when a borrower defaults. This raises the marginal benefit of lowering the default probability and induces the intermediary to tighten $q$. According to (7), the intermediary does not tighten underwriting indefinitely. A higher $q$ is costly to implement and reduces the number of originated loans by lowering the approval rate and application demand. Therefore, underwriting becomes stricter until the additional reduction in default losses is offset by the higher underwriting costs and lost lending margins.

Capital requirements enter as an additional marginal cost of lending, which corresponds to an increase in $R^f$ in this setting. Banks respond to the higher cost by raising loan rates. As shown above, a higher loan rate increases the benefit of reducing default risk and therefore leads banks to tighten underwriting. Capital regulation thus affects both the price of bank credit and the risk composition of bank originations. This prediction is also consistent with the empirical evidence in Section 2.4.2, where bank approval rates decline as capital regulation tightens.

## 3.4. Default Loss Internalization

In the static model, I assume that the lender fully internalizes default losses when maximizing profit. In practice, however, the extent to which intermediaries internalize default losses can differ across intermediaries. Limited liability implies that intermediary owners need not absorb the full losses in sufficiently adverse states. Such incentives also depend on their business models, franchise value, and incentives to preserve continuation value. This motivates introducing a wedge that captures the share of default losses internalized by the intermediary.

The wedge is important for differentiating banks and NBFIs. Banks derive franchise value from operating across multiple business lines. Kim et al. (2022) emphasize that banks tend to operate in several business areas, while NBFIs are more likely to focus on a single line of business. As a result, the costs that banks perceive from defaults are higher than those perceived by NBFIs, as banks need to take into account their other business lines and have stronger incentives to internalize default losses. However, NBFIs have fewer additional business profits and less franchise value to protect, so the costs of defaults they internalize are smaller.

In the general equilibrium model, I capture these differences through $\kappa_j$. The parameter $\kappa_j$ measures the share of the default loss, $d_j(q_j)R_j^\ell$, absorbed by intermediary $j$. The expected payoff per dollar of lending is therefore $(1-\kappa_j d_j(q_j))R_j^\ell$. A higher $\kappa_j$ means that borrower default has a larger effect on the intermediary's profits and net worth, strengthening its incentive to tighten underwriting and increase the loan rate. The differences between banks and NBFIs described above therefore imply $\kappa_B > \kappa_{NB}$, which contributes to the differences in underwriting standards.[19]

# 4. The Quantitative Model

In this section, I build a general equilibrium model to formalize the mechanism through which bank capital requirements affect the allocation of credit across banks and NBFIs. To this end, I use the model as a laboratory to quantify the effects of tighter regulation on credit losses and financial intermediation in counterfactual financial stress scenarios.

I extend the partial-equilibrium intermediary framework and embed banks and NBFIs as credit suppliers, with each sector jointly choosing loan rates and underwriting standards. I embed these intermediaries in a saver–borrower general equilibrium framework of Curdia and Woodford (2010) and Eggertsson et al. (2024), in which borrowers allocate applications across the two sectors in response to their lending terms. Savers provide funding to both intermediary sectors by holding deposits and money market funds, as in Begenau and Landvoigt (2022). The production side consists of intermediate-good producers subject to nominal rigidities, and a monetary authority sets the policy rate.

[19] This interpretation is also consistent with Bosshardt et al. (2025), who find that banks charge more for observable default risk than NBFIs even for loans sold into the same GSE market.

## 4.1. Banks

I extend the partial-equilibrium intermediary block to a banking sector, in which a continuum of banks indexed by $b$ fund lending with deposits, hold liquid securities, and internalize regulatory-capital costs when setting loan rates and underwriting standards. For notational simplicity, I suppress the index $b$ and mark bank-specific objects with the subscript $B$. Banks post the loan rate $R^{\ell}_{B,t}$ and choose underwriting stringency $q_{B,t}$. As described in the partial-equilibrium block, originations are the product of the approval rate and loan applications,

$$L_{B,t} = p_B(q_{B,t})\, L^{app}_{B}(R^{\ell}_{B,t}, p_B(q_{B,t})). \tag{8}$$

Similarly, $d_B(q_{B,t})$ and $s_B(q_{B,t})$ denote the corresponding default rate and per-dollar underwriting cost. The bank originates loans $L_{B,t}$ and holds liquid securities $S_{B,t}$, financed by deposits $D_{B,t}$ and predetermined equity $E_{B,t}$,

$$L_{B,t} + S_{B,t} = D_{B,t} + E_{B,t}. \tag{9}$$

Liquid securities earn the gross policy rate $R_t$. Following Drechsler et al. (2017), banks exercise market power in the deposit market and face the deposit supply schedule

$$D_{B,t} = D_B(R^{D}_{B,t}). \tag{10}$$

Given these balance-sheet constraints, the bank chooses the loan rate $R^{\ell}_{B,t}$, underwriting stringency $q_{B,t}$, the amount of security holdings $S_{B,t}$, and the deposit rate $R^{D}_{B,t}$ at date $t$. Loans, securities, and deposits chosen at date $t$ settle at date $t+1$. Then, I can express the pre-dividend profit as

$$\text{Profit}_{B,t} = \Big((1-\kappa_B d_B(q_{B,t}))R^{\ell}_{B,t} - s_B(q_{B,t})\Big)\, L_{B,t} + R_t S_{B,t} - R^{D}_{B,t} D_{B,t} - c_B(L_{B,t}, E_{B,t}; \nu).$$

Banks internalize a share $\kappa_B < 1$ of default losses, as discussed in Section 3.4. Limited liability places a limit on the losses that are absorbed through bank profits and net worth. The remaining share is not absorbed within the bank and is instead borne directly by savers. In particular, the fraction $1-\kappa_B$ enters the saver budget constraint as a lump-sum charge. Capital regulations are captured by $c_B(L_{B,t}, E_{B,t}; \nu)$ as an adjustment cost, which is discussed in the next paragraph. At date $t+1$, after the payoff from the date-$t$ portfolio is realized and dividends are paid, bank equity evolves according to

$$E_{B,t+1} = \text{Profit}_{B,t} - \gamma_B E_{B,t}.$$

The term $\gamma_B E_{B,t}$ captures dividends, assumed to be a constant fraction $\gamma_B \in (0,1)$ of beginning-of-period bank equity.

**Capital Requirement.** Gerali et al. (2010), Ulate (2021), and Balloch and Koby (2023) motivate modeling capital requirements as a balance-sheet adjustment cost that reflects the resources associated with external equity issuance or portfolio restructuring as banks approach the regulatory threshold. The functional form of the capital-requirement cost follows Balloch and Koby (2023)

$$c_B(L, E; \nu) = \xi \frac{E}{E/L - \nu}. \tag{11}$$

$\nu$ captures the required capital ratio set by the regulatory authority, and $\xi$ captures the extent to which the regulated intermediary perceives the regulation as a cost. I adopt this specification for two reasons. First, Begenau et al. (2026) document that regulatory capital constraints rarely bind strictly for U.S. bank holding companies. The vast majority of banks maintain capital buffers above the regulatory minimum.[20] This evidence suggests that banks generally adjust before violating the regulatory threshold, which motivates representing capital regulation as a marginal cost that rises sharply as the bank approaches the threshold rather than as a constraint that is routinely violated. Second, Balloch and Koby (2023) highlight that equation (11) provides a smooth approximation to a hard risk-based capital constraint, such as $E \geq \nu L$. In the model, loans receive a unit regulatory weight, while the liquid securities considered here are assigned a zero regulatory weight. The model counterpart of the regulatory capital ratio is therefore $E/L$.

**First Order Conditions.** Banks choose $R^{\ell}_{B,t}$, $R^{D}_{B,t}$, $S_{B,t}$, and $q_{B,t}$ to maximize profit under the constraints (8), (9) and (10). At the symmetric equilibrium, the optimal loan rate satisfies

$$R^{\ell}_{B,t} = \frac{\epsilon^{\ell}_B}{\epsilon^{\ell}_B - 1} \frac{1}{1 - \kappa_B d_B(q_{B,t})} \left(R_t + s_B(q_{B,t}) + c_{B,L}(L_{B,t}, E_{B,t}; \nu)\right), \tag{12}$$

where $\epsilon^{\ell}_B$ is the loan-rate elasticity of application demand and $c_{B,L} \equiv \partial c_B / \partial L_{B,t}$ is the marginal regulatory-capital cost of originating an additional dollar of loans. The optimal underwriting standard satisfies

$$-\kappa_B d'_B(q_{B,t}) R^{\ell}_{B,t} = s'_B(q_{B,t}) - \Big((1 - \kappa_B d_B(q_{B,t})) R^{\ell}_{B,t} - R_t - s_B(q_{B,t}) - c_{B,L}(L_{B,t}, E_{B,t}; \nu)\Big) \left(\frac{p'_B(q_{B,t})}{p_B(q_{B,t})} + \chi^q_B\right), \tag{13}$$

where $\chi^q_B \equiv d \log L^{app}_B(R^{\ell}_{B,t}, p_B(q_{B,t}))/dq_{B,t}$. The last two terms capture the effects of underwriting stringency on origination volume through the approval rate and bank application demand,

[20]Even at the height of the global financial crisis, more than 90 percent of banks were classified as well capitalized according to their Tier 1 capital ratios, while approximately 5 percent fell below the regulatory minimum.

respectively. Finally, at the symmetric equilibrium, the optimal deposit rate satisfies

$$R^D_{B,t} = \frac{\epsilon^{\mathcal{D}}}{1+\epsilon^{\mathcal{D}}} R_t, \tag{14}$$

where the deposit-supply elasticity is defined as $\epsilon^{\mathcal{D}} \equiv \partial \log D_B(R^D)/\partial \log R^D$.

## 4.2. NBFIs

NBFIs are monopolistically competitive loan intermediaries that originate loans but cannot issue insured deposits. Instead, they finance lending through wholesale funding and operate outside the regulatory perimeter. The NBFI sector consists of a continuum of intermediaries indexed by $n$. As with banks, I focus on a symmetric equilibrium, suppress the individual NBFI index $n$, and use the subscript $NB$ to denote NBFI-sector variables. The representative NBFI posts the loan rate $R^{\ell}_{NB,t}$ and chooses an underwriting stringency $q_{NB,t}$, and originations are again the product of the approval rate and loan applications,

$$L_{NB,t} = p_{NB}(q_{NB,t})\, L^{app}_{NB}(R^{\ell}_{NB,t}, p_{NB}(q_{NB,t})). \tag{15}$$

The functions $d_{NB}(q_{NB,t})$ and $s_{NB}(q_{NB,t})$ are the associated default rate and per-dollar underwriting cost. Unlike banks, the NBFI holds no securities and issues no deposits. It funds loans with wholesale funding $F_{NB,t}$ and predetermined equity $E_{NB,t}$,[21]

$$L_{NB,t} = F_{NB,t} + E_{NB,t}. \tag{16}$$

The NBFI chooses the loan rate $R^{\ell}_{NB,t}$, underwriting stringency $q_{NB,t}$, and wholesale funding $F_{NB,t}$ at date $t$. Loans and wholesale funding chosen at date $t$ settle at date $t+1$. I express the associated pre-dividend payoff from the date-$t$ portfolio as

$$\text{Profit}_{NB,t} = \Big((1-\kappa_{NB} d_{NB}(q_{NB,t}))R^{\ell}_{NB,t} - s_{NB}(q_{NB,t})\Big)\, L_{NB,t} - R^F_t F_{NB,t}.$$

NBFIs take $R^F_t$ as given. The parameter $\kappa_{NB}$ denotes the share of default losses absorbed through NBFI profits and net worth based on the discussion in Section 3.4.[22] The remaining share, $1-\kappa_{NB}$, is borne by savers, who hold money market funds for liquidity purposes, and enters their budget

[21] As in Buchak et al. (2024), NBFIs can also be financed by banks through secondary markets. In other words, NBFIs originate loans and issue securities that banks hold, so that banks indirectly fund NBFI lending. Banks also support NBFIs through credit lines (Jiang 2023; Acharya et al. 2026). This extension is discussed in Section 6.2.

[22] Because the model abstracts from the explicit sale and securitization of individual mortgages, $\kappa_{NB}$ should not be interpreted as the fraction of originated loans retained by the originating NBFI.

constraint as a lump-sum charge. The underwriting cost associated with the date-$t$ portfolio is expressed in the same date-$t$ units and is settled with the portfolio at date $t+1$. At date $t+1$, after the payoff from the time $t$ portfolio is realized and dividends are paid, NBFI equity evolves according to

$$E_{NB,t+1} = \text{Profit}_{NB,t} - \gamma_{NB} E_{NB,t}.$$

where $\gamma_{NB} E_{NB,t}$ captures dividends paid by NBFIs to savers, with $\gamma_{NB} \in (0,1)$.

**First Order Conditions.** NBFIs choose $R^{\ell}_{NB,t}$, $F_{NB,t}$, and $q_{NB,t}$ to maximize profit under the constraints (15) and (16). At the symmetric equilibrium, the optimal loan rate satisfies

$$R^{\ell}_{NB,t} = \frac{\epsilon^{\ell}_{NB}}{\epsilon^{\ell}_{NB} - 1} \frac{1}{1 - \kappa_{NB} d_{NB}(q_{NB,t})} \left( R^F_t + s_{NB}(q_{NB,t}) \right), \tag{17}$$

where $\epsilon^{\ell}_{NB}$ is the loan-rate elasticity of application demand, with $\epsilon^{\ell}_{NB} > 1$ under monopolistic competition. Relative to the bank pricing condition (12), the NBFI marginal cost replaces the policy rate and regulatory-capital cost with the wholesale funding rate $R^F_t$, reflecting its position outside the regulatory perimeter. The optimal underwriting standard satisfies

$$-\kappa_{NB} d'_{NB}(q_{NB,t}) R^{\ell}_{NB,t} = s'_{NB}(q_{NB,t}) - \left( (1 - \kappa_{NB} d_{NB}(q_{NB,t})) R^{\ell}_{NB,t} - R^F_t - s_{NB}(q_{NB,t}) \right) \left( \frac{p'_{NB}(q_{NB,t})}{p_{NB}(q_{NB,t})} + \chi^q_{NB} \right), \tag{18}$$

where $\chi^q_{NB} \equiv d \log L^{app}_{NB} \left( R^{\ell}_{NB,t}, p_{NB}(q_{NB,t}) \right) / dq_{NB,t}$. The last two terms capture the effects of underwriting stringency on origination volume through the approval rate and NBFI application demand, respectively.

## 4.3. Borrowers

The borrower consists of a continuum of ex ante identical households of measure $\chi$. At date $t$, the representative borrower household chooses consumption $C^b_t$, labor supply $N^b_t$, and total loan applications $L^{app}_t$. Before applications are submitted, each lender posts loan rates and chooses an underwriting standard. Household members observe the posted rates and each sector's approval probabilities, but not their individual approval outcomes or the exact underwriting standard. They choose either a bank or an NBFI based on these terms and idiosyncratic application preferences. Appendix E provides the aggregation procedure.

### 4.3.1. Preferences and total applications

The representative borrower household solves the following problem with GHH preferences (Greenwood et al. 1988). For $\sigma \neq 1$,

$$\max_{\{C_t^b, N_t^b, L_t^{app}\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^b)^t \mathcal{U}(C_t^b, N_t^b) \quad \text{where} \quad \mathcal{U}(C_t^b, N_t^b) = \frac{1}{1-\sigma}\left[C_t^b - \Xi_b \frac{{N_t^b}^{1+\phi}}{1+\phi}\right]^{1-\sigma}.$$

When $\sigma = 1$, utility takes the logarithmic form. Borrowing is subject to a loan-to-income constraint at the application stage,

$$L_t^{app} \leq \theta W_t N_t^b.$$

The variable $L_t^{app}$ denotes the aggregate face value submitted at the application stage, and originated borrowing is determined after lender choice and underwriting. The budget constraint is explained after describing the allocation of loan applications and their settlement.

### 4.3.2. Application allocation

At date $t$, given the loan application amount $L_t^{app}$, each member $i$ of a continuum of household members, whose creditworthiness $x_i$ follows a distribution $F(x)$, selects one lender and submits a single application. Before submitting an application, applicant $i$ observes each lender's posted loan rate $R_{k,j}^{\ell}$ and approval probability $p_{k,j}(q_{k,j})$, but not the lender's internal underwriting standard $q_{k,j}$ or the applicant's individual approval outcome. The applicant also draws lender-specific application preference shocks $e_{i,k,j} > 0$ from a nested Fréchet distribution as in Herreño (2023). This captures non-price attributes such as accessibility, convenience, and prior experience with a lender. The upper level of the nested structure distinguishes the bank and NBFI sectors, while the lower level differentiates lenders $k \in \mathcal{K}_j$ within each sector $j \in \{B, NB\}$.

In the model, application preference shocks are independent of creditworthiness. Therefore, application allocation preserves the underlying creditworthiness distribution at every lender.

Assumption 1. *Application preference shocks are independent of applicant creditworthiness:*

$$\left\{e_{i,k,j}\right\}_{k \in \mathcal{K}_j,\, j \in \{B,NB\}} \perp x_i, \qquad x_i \sim F(x).$$

This restriction provides a baseline consistent with the limited differences in observable applicant characteristics documented in Section 2.3. To incorporate borrowers' sorting on unobservables, this assumption is relaxed in Section 6.2, which introduces heterogeneous borrower types that differ in their sensitivity to approval standards and in their performance under the same screening technology.

In a sector-symmetric equilibrium, where $R^{\ell}_{k,j,t} = R^{\ell}_{j,t}$ and $q_{k,j,t} = q_{j,t}$, the resulting sector-$j$ application share is

$$\omega_{j,t} = \frac{\psi_j \left[p_j(q_{j,t})\right]^{\eta} \left(R^{\ell}_{j,t}\right)^{-\varphi}}{\sum\limits_{m \in \{B,NB\}} \psi_m \left[p_m(q_{m,t})\right]^{\eta} \left(R^{\ell}_{m,t}\right)^{-\varphi}}. \tag{19}$$

Here, $\psi_j > 0$, with $\psi_B + \psi_{NB} = 1$, captures the non-price attractiveness of sector $j$. The parameter $\varphi$ governs substitution across sectors in response to loan rates, while $\eta$ governs the response of applications to approval probabilities. Appendix E provides the full distributional specification and derives the application choice probabilities. Sector $j$ therefore receives a volume of applications

$$L^{app}_{j,t} = \omega_{j,t} L^{app}_t$$

to process. When tighter bank capital requirements raise the bank loan rate and reduce the bank approval probability, the bank option becomes less attractive, leading more borrowers to direct their initial applications to NBFIs with raising $\omega_{NB}$.

#### 4.3.3. Application to Origination

After applications are assigned, lender $k$ applies its underwriting standard, and its origination amount is $L^{orig}_{k,j,t} = p_j(q_{k,j,t})L^{app}_{k,j,t}$. At the symmetric equilibrium, sector-level originations are $L^{orig}_{j,t} = p_j(q_{j,t})L^{app}_{j,t} = p_j(q_{j,t})\omega_{j,t}L^{app}_t$.

The model assumes that denied applicants do not resubmit another application. The reason is twofold. First, if reapplication is allowed under both the loose- and tight-regulation regimes, the model predicts that the aggregate NBFI approval rate increases as bank regulation tightens. When banks tighten their underwriting standards, the set of applicants who are denied by banks but still satisfy the NBFI cutoff expands. Since these borrowers satisfy NBFI rules, additional reapplications by those borrowers eventually increase the aggregate NBFI approval rate. However, the empirical analysis does not show such an increase in the NBFI approval rate.

Second, there is direct evidence that mortgage rejection can generate meaningful delays and costs in subsequent applications. Ky and Lim (2022) emphasize that mortgage denial can remain economically consequential even when the applicant is subsequently approved by another lender or for another product. Delays in securing financing can cause the applicant to lose the intended home purchase, while alternative mortgage products may involve higher borrowing costs. Thus, eventually obtaining credit elsewhere is not necessarily an immediate and equivalent substitute for approval of the original application.

A 2022 Freddie Mac survey of borrowers denied a mortgage within the previous four years finds that some denied borrowers had not reapplied and did not plan to reapply within the following two years, often while addressing credit score or making adjustments to the application, including downpayment constraints. Reapplication also entails additional search costs. Agarwal et al. (2024) estimate that an additional mortgage search costs, on average, the equivalent of 29.7 basis points in the loan rate.

To incoporate the case where some rejected borrowers do reapply, Section 6.2 relaxes this assumption by allowing applicants rejected by banks to submit an additional application to an NBFI after taking into account the cost of further search. Allowing for reapplication weakens the effects of tighter capital requirements on both the aggregate default rate and total defaulted payments, but does not overturn the main result that tighter bank capital regulation increases aggregate credit risk.

#### 4.3.4. Settlement, Default, and Budget Constraint

At date $t+1$, borrowers with loans originated at $t$ receive idiosyncratic repayment shocks and default when realized repayment capacity falls below a fixed threshold.[23] The emphasis on repayment capacity is motivated by Gerardi et al. (2018), who show that changes in households' ability to pay are important determinants of mortgage default. This specification isolates the effect of underwriting on the risk composition of originated loans. The assumption that the loan rate $R^{\ell}$ does not directly affect default outcomes is motivated by empirical evidence showing that loan rates have a limited direct effect on default incidence. Foote et al. (2008) show that adjustable-rate mortgage borrowers who defaulted did so before their interest rates reset, suggesting that higher interest rates were not the primary trigger of default. Bosshardt et al. (2025) use variation in upfront guarantee fees for fixed-rate mortgages as an instrument for mortgage rates and find that the direct effect of higher interest rates on default is small and statistically insignificant.

Aggregating individual default incidence over the distribution of approved borrowers' creditworthiness and the repayment shocks, the default rate under underwriting stringency $q_{j,t}$ is summarized by $d_{j,t} = d_j(q_{j,t})$, with $d_j'(q_{j,t}) < 0$. The derivation is provided in Appendix F.[24]

[23] Repayment capacity is loan-specific rather than household labor income, and I assume that household consumption, labor supply, and transfers cannot alter individual default outcomes. This reduced-form treatment of loan payments is related to Iacoviello (2015), while underwriting here changes default risk through borrower selection.

[24] One thing to note is that the derivation relies on Assumption 1, under which application preference shocks are drawn independently of applicants' creditworthiness. This implies that, conditional on applying to a sector, underwriting stringency determines the creditworthiness distribution of approved borrowers. The rationale for this assumption comes from the empirical findings in Section 2.3, which show that observable risk differences emerge primarily after applications are screened.

Taking default into account, the borrower budget constraint can be derived as

$$P_t C_t^b + (1 - d_{t-1})\, R_{t-1}^{\ell} L_{t-1}^{orig} = W_t N_t^b + L_t^{orig} \tag{20}$$

where $R_t^{\ell}$ is the aggregate loan-rate index and the repayment wedge $d_t$ is defined implicitly by

$$(1 - d_t)\, R_t^{\ell} L_t^{orig} = \sum_j \left(1 - d_{j,t}\right) R_{j,t}^{\ell} L_{j,t}^{orig}. \tag{21}$$

Only approved loans enter $L_t^{orig}$ and provide resources for household consumption at date $t$, while payments on these loans are due at $t + 1$. Rejected applications provide no resources and create no repayment obligations, but rejected members share household consumption with approved members.

Lastly, default appears in two ways. First, the defaulted repayment represents a financial loss borne by the financial intermediaries and the savers. Given the amount of default, it is allocated between intermediaries and savers through $\kappa_j$ and $1-\kappa_j$. Second, it entails an additional deadweight resource cost equal to $\zeta \sum_{j\in\{B,NB\}} d_{j,t} L_{j,t}$. This term represents real resources destroyed in default resolution, including legal and recovery costs. This reduced-form measure is distinct from the default that is transferred between borrowers and savers in that this cost is a direct destruction of aggregate resources rather than a financial transfer between private agents. This deadweight cost is borne directly by the saver as a lump-sum charge.

## 4.4. Savers

Savers constitute a continuum of infinitely lived households of measure $1 - \chi$ in the economy. A representative saver maximizes expected lifetime utility

$$\max_{\{C_t^s, N_t^s, B_t, D_t, F_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^s)^t \left[ \mathcal{U}(C_t^s, N_t^s) + \Xi_L \mathcal{L}\left(\frac{D_t}{P_t}, \frac{F_t}{P_t}\right)\right], \tag{22}$$

subject to the budget constraint

$$P_t C_t^s + B_t + D_t + F_t + T_t + \Psi_t^D = W_t N_t^s + R_{t-1} B_{t-1} + R_{t-1}^D D_{t-1} + R_{t-1}^F F_{t-1} + \mathrm{Div}_t^s. \tag{23}$$

by choosing consumption $C_t^s$, labor $N_t^s$, and financial vehicles. $B_t$, $D_t$, and $F_t$ denote holdings of bonds, bank deposits, and money market fund claims that finance NBFIs, respectively. $W_t$ denotes the nominal wage and $\mathrm{Div}_t^s$ collects profit income from intermediate-good firms, banks, and NBFIs.

$T_t$ captures the lump-sum charges associated with defaults by the two financial intermediaries that are not internalized by the financial sector.

$$T_t = \sum_{j\in\{B,NB\}} (1-\kappa_j)\, d_{j,t-1}\, R^{\ell}_{j,t-1}\, L^{orig}_{j,t-1}. \tag{24}$$

For loans originated by intermediary $j$, the fraction $\kappa_j$ is absorbed by intermediary equity, while the remaining fraction $1-\kappa_j$ is borne directly by savers through claims they hold.[25] Because savers also own banks and NBFIs, losses absorbed by intermediary equity can still reduce their dividend income and wealth. $\Psi^D_t$ captures the resource costs associated with default, such as legal and recovery costs, and is defined as

$$\Psi^D_t \equiv \zeta\left[d_{B,t-1}L_{B,t-1} + d_{NB,t-1}L_{NB,t-1}\right].$$

I assume GHH preferences (Greenwood et al. 1988) as in the borrower block. Real liquidity services are provided by a CES aggregate of deposits and MMF claims. Feenstra (1986) shows that introducing liquidity services directly into utility is isomorphic to specifying money demand in the presence of transaction costs. Following Begenau and Landvoigt (2022), deposits and MMF claims are imperfect substitutes because both provide low-risk and liquid transaction services. I capture this imperfect substitutability using the following CES liquidity aggregator

$$\mathcal{L}\left(\frac{D_t}{P_t},\frac{F_t}{P_t}\right) = \left[\alpha\left(\frac{D_t}{P_t}\right)^{\frac{\vartheta-1}{\vartheta}} + (1-\alpha)\left(\frac{F_t}{P_t}\right)^{\frac{\vartheta-1}{\vartheta}}\right]^{\frac{\vartheta}{\vartheta-1}}, \qquad \alpha\in(0,1), \quad \vartheta>0, \tag{25}$$

where $\vartheta$ denotes the elasticity of substitution between deposits and MMF claims. The aggregate quantity of liquid claims is determined by intermediary balance sheets, while savers choose their composition conditional on equilibrium liquidity availability. Combining the first-order conditions for $D_t$ and $F_t$ gives

$$\frac{D_t/P_t}{F_t/P_t} = \left(\frac{\alpha}{1-\alpha}\frac{R_t - R^F_t}{R_t - R^D_t}\right)^{\vartheta}. \tag{26}$$

Equation (26) describes the household's portfolio allocation between two liquid liabilities, bank deposits and the short-term funding of NBFIs. Each spread against the policy rate measures the financial return forgone in exchange for the liquidity services provided by the corresponding instrument. When the deposit spread $R_t - R^D_t$ widens relative to the MMF spread $R_t - R^F_t$, deposits become more costly to hold and households shift toward MMFs.

[25]If the government guarantees transferred claims, it compensates claim holders and finances the guarantee with taxes on saver households. The resulting burden on savers is equivalent to their absorbing the losses on the transferred claims directly.

## 4.5. Rest of the Standard New Keynesian Block

Intermediate-good producers are monopolistic competitors with a linear production technology, so real marginal cost is equal to the real wage divided by aggregate productivity. Nominal rigidities are introduced following Calvo (1983). The production block then provides the New Keynesian Phillips Curve, whose log-linearized version is

$$\pi_t = \kappa_\pi mc_t + \beta_s \mathbb{E}_t \pi_{t+1}. \tag{27}$$

where $mc_t$ denotes the log deviation of real marginal cost from its steady state and $\pi_t$ denotes the log-linearized gross inflation rate, where $\Pi_t = P_t/P_{t-1}$. The discount factor $\beta_s$ is used because intermediate-good firms are owned by savers, and therefore future profits in the firms' price-setting problem are discounted using the savers' discount factor. The steady-state inflation rate is zero, so the steady-state gross inflation rate is one.

Monetary policy sets the nominal interest rate using a Taylor-type rule with interest-rate smoothing and an exogenous policy shock,

$$\frac{R_t}{\bar{R}} = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\rho_R} \left(\left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi_\pi} \left(\frac{Y_t}{\bar{Y}}\right)^{\phi_y}\right)^{1-\rho_R} \exp(\varepsilon_t^R). \tag{28}$$

**Market clearing.** The labor market clears when total labor demand equals the sum of saver and borrower labor supplies. The goods market clears when output covers total consumption together with the real resources spent on intermediation. Define the resource costs of financial intermediation associated with the portfolio as

$$\Psi_t^I \equiv s_B(q_{B,t-1})L_{B,t-1} + s_{NB}(q_{NB,t-1})L_{NB,t-1} + c_B\left(L_{B,t-1}, E_{B,t-1}; \nu\right),$$

where $\Psi_t^I$ collects the resources used for underwriting and the capital-regulation friction. The goods market clearing condition can then be written compactly as

$$Y_t = (1-\chi)C_t^s + \chi C_t^b + \frac{\Psi_t^I + \Psi_t^D}{P_t}. \tag{29}$$

Underwriting standards consume resources in proportion to originated lending in each sector, while the capital-regulation friction also absorbs resources. These costs are summarized by $\Psi_t^I$. Default entails additional resource costs summarized by $\Psi_t^D$ as discussed in Section 4.3.4.

# 5. Calibration

This section describes the calibration strategy. I calibrate the model to the U.S. economy at a quarterly frequency. I first discuss the parameters that are set externally. I then explain the remaining parameters that are relevant to sector-level moments for banks and NBFIs, with particular emphasis on approval rates, default rates, and verification costs.

## 5.1. Externally Calibrated Parameters

**Household.** The saver discount factor $\beta_s$ is calibrated to match a 2% annual policy rate, and the borrower discount factor $\beta_b$ is set to match a 6.3% annual discount rate following Gatt (2025). Both agents' intertemporal elasticities are set to one, $\sigma_s = \sigma_b = 1$. The inverse labor supply elasticity is set to $\phi = 2/3$ as in Herreño and Pedemonte (2025). The labor-disutility weights, $\Xi_s$ and $\Xi_b$, are chosen so that steady-state labor equals 1/3 for each type, and the borrower population share is $\chi = 0.39$ following Iacoviello (2005).

**Saver Liquidity Preference.** The saver deposit weight $\alpha$ matches a steady-state deposit-to-money-fund ratio of 3.58 in 2019 (Im et al. 2025). The elasticity of substitution between deposits and money-market funds is calibrated as $\vartheta = 3.17$ following d'Avernas and Vandeweyer (2024).

**Borrower Application.** The response of applications to approval probabilities, governed by $\eta$, is disciplined by the search logic of Agarwal et al. (2024). In their model, the expected benefit of an application is the approval probability times the surplus conditional on approval. I carry this proportionality into the allocation rule by setting $\eta = 1$.[26]

The bank–NBFI loan substitution elasticity is set to $\varphi = 8$. Buchak et al. (2024) estimate the substitution between information-sensitive loans and information-insensitive loans to be 8.03. I further discipline this parameter using the application-level evidence in my sample. Reduced-form regressions of relative bank–NBFI application volumes on relative approval probabilities and relative loan rates imply values of $\varphi$ between approximately 6 and 11 across alternative specifications, reported in Appendix G.3. Based on both the existing literature and this empirical evidence, I choose $\varphi = 8$ as the baseline value, which lies at the lower end of the range implied by my estimates. A sensitivity analysis over $\varphi$, together with $\eta$, confirms that the key results are robust across the range. Results are presented in Appendix H.1.

[26]This is a reduced-form mapping rather than a derivation from the application-allocation block. In the search model of Agarwal et al. (2024), the expected benefit of an application is the approval probability times the surplus conditional on approval, so it scales in proportion to approval rate $p_j$. In my allocation rule, approval access enters as the separate demand shifter $[p_j(q_j)]^\eta$, and setting $\eta = 1$ makes application flows scale one-for-one with approval access, matching that proportionality.

I set $\epsilon_B^\ell = \epsilon_{NB}^\ell = 360$, following Ulate (2021) and Abadi et al. (2023).[27] The loan-to-income limit is $\theta = 1.9$ (Campbell and Cocco 2015), adjusted with HMDA. The bank loan-preference weight, $\psi_B = 0.43$, matches the share of bank applications in HMDA after accounting for the steady-state approval rates and loan rates in each sector.

**Financial Intermediaries.** The equity-payout parameters $\gamma_B$ and $\gamma_{NB}$ match the sectoral equity-to-loan ratios, 0.164 for banks and 0.249 for NBFIs (Jiang 2023), conditional on the capital-requirement cost scale $\xi = 0.0012$ (Ulate 2021) and the requirement $\nu = 0.06$. For deposit market power, I set $\epsilon^{\mathcal{D}} = 269.5$ following Ulate (2021).

**Nonfinancial Intermediaries.** For the New Keynesian block, the elasticity of substitution among intermediate goods, $\theta_{\text{prod}}$, is set to 3.9, following Abadi et al. (2023), and the Phillips-curve slope, $\kappa_\pi$, is set to 0.0062, as estimated by Hazell et al. (2022). The Taylor-rule parameters are based on Hofmann et al. (2024), $\rho_R = 0.72$, $\phi_\pi = 2.11$, and $\phi_y = 0.26$. Externally calibrated parameters are summarized in Appendix Table A2.

## 5.2. Internally Calibrated Parameters

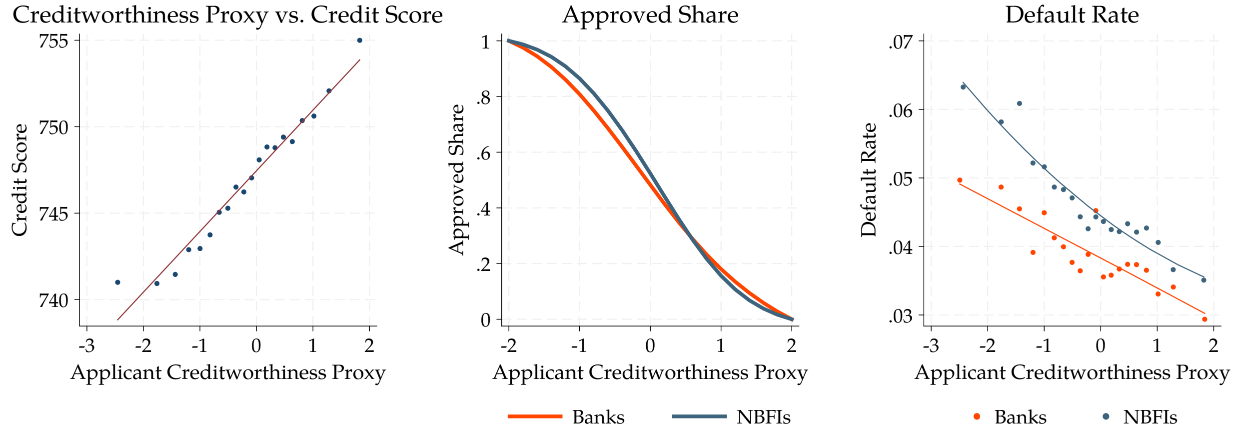
The remaining parameters govern each lender's approval decision, default, screening costs, and the share of default losses internalized by each intermediary.

Because underwriting standards $q$ are not directly observed, I first construct an applicant quality index $x$ as the first principal component of income, the debt-to-income ratio, and loan amount using the HMDA dataset, as in Section 2.3.2. The index is normalized so that higher values indicate *safer* observable applicant profiles. While the index omits credit scores because they are unavailable in HMDA, I merge HMDA with GSE data that report credit scores following Buchak and Jørring (2026) and show that the measure I construct is strongly positively correlated with credit scores, as shown in the first panel of Figure 6. Using this index, I first calibrate the parameters relevant to approval and default. Given these parameters, I then back out the screening cost and default-loss retention parameters from the optimality conditions of the lender's decision.

**Evidence from the Data** Figure 6 provides empirical evidence on the applicant creditworthiness measure by comparing it with credit scores and also shows the shapes of the two schedules that motivate the functional forms used in the quantitative model.

[27] Note that $\epsilon$ (within-sector) and $\varphi$ (bank–NBFI) are both defined over *gross* interest rates but capture different objects, substitution within sectors and substitution between sectors, respectively. Their magnitudes are therefore not comparable. Single-digit values for substitution within sector calculated using net rates, such as 5 in Gerali et al. (2010), are likewise not directly comparable. For context, evaluated at the steady-state loan rate, the baseline gross-rate elasticity of 360 implies a local net-rate elasticity of approximately 5.4. This confirms that the baseline calibration is in the same ballpark as the single-digit net-rate elasticities typically used in the literature (e.g., Frame et al. 2026).

**Figure 6.** Applicant Creditworthiness Proxy and Credit Score, Approval, and Default




The first panel compares the applicant creditworthiness measure I construct using HMDA information with credit scores after merging HMDA with the GSE dataset. The measure has a strong positive linear correlation with credit scores even though HMDA does not report credit scores. The second panel of Figure 6 reports, for each value of applicant creditworthiness, the share of applicants who would be approved if the approval cutoff were set at that value. The third panel plots subsequent loan default against borrower creditworthiness using HMDA applications matched to GSE loan-performance data. Default declines with borrower creditworthiness over the empirical support. This relationship motivates a decreasing and approximately log-linear local default schedule, $d(q)$.

**Approval Schedule** The approval schedule is assumed to follow

$$p_j(q) = \frac{1}{1 + b_{0,j} \exp\left(b_{1,j} q\right)}, \qquad j \in \{B, NB\},$$

where $b_{1,j} > 0$. A higher $q$ represents stricter underwriting and implies a lower approval probability. The logistic functional form is motivated by the pattern shown in Figure 6 and can be derived by assuming that applicant creditworthiness is logistically distributed. This distributional assumption is consistent with Ouazad and Rancière (2016).

Because underwriting stringency $q$ is not directly observed, I construct its empirical counterpart by using applicant creditworthiness $x$ and observed approval decisions to recover the approval cutoff that best separates approved from denied applications. Specifically, I rank applications by $x$ and choose the cutoff $\hat{q}$ that minimizes the misclassification error, following Manski (1975). I implement this procedure separately for each lender-county-year cell $g$, yielding an estimated cutoff $\hat{q}_g$. A higher $\hat{q}_g$ indicates stricter underwriting, and I use this measure as the empirical counterpart of the underwriting choice $q$ in the model for each sector.[28]

I then use $\hat{q}_g$ and observed approval probabilities to calibrate $b_{0,j}$ for each sector. The basic idea is to use the common underwriting measure constructed above to estimate the relationship between underwriting stringency and approval probabilities. I first estimate the log-odds relationship implied by the logistic approval schedule using the cell-level approval rate and the estimated underwriting stringency

$$\log\left(\frac{P_g}{1-P_g}\right) = \gamma_j \hat{q}_g + \mu_{\ell,m} + \tau_{m,t} + \varepsilon_g,$$

where $\hat{q}_g$ is the estimated underwriting-policy location in cell $g$ and $P_g$ is the approval rate in the same cell. I include lender-by-county fixed effects $\mu_{\ell,m}$ and county-by-year fixed effects $\tau_{m,t}$. Under this common-scale normalization, the model implies $\gamma_j = -b_{1,j}$.

I calculate the sector-level underwriting standard $q_j$ as the simple average of the estimated cutoffs $\hat{q}_g$ within each sector, $q_j = \frac{1}{N_j}\sum_{g\in\mathcal{G}_j} \hat{q}_g$, and use this average as the empirical target for the model's steady-state underwriting standard. Finally, I calibrate $b_{0,j}$ so that the approval schedule evaluated at $q_j$ matches the observed approval rate in each sector. The target approval rates are 80.13 percent for banks and 88.09 percent for NBFIs. I focus here on the main intuition, while Appendix G provides the full estimation procedure and additional details.

**Default Schedule** As discussed in Section 4.3.4, the model summarizes default rate as a function of underwriting stringency. I specify the default schedule as

$$d_j(q) = \delta_{0,j}\exp\left(-\delta_{1,j}q\right), \qquad d_j'(q) < 0. \tag{30}$$

There are two reasons for using this exponential function specification. First, the loan-level data show that subsequent default declines approximately exponentially with borrower creditworthiness as shown in Figure 6. Second, the repayment specification links borrower creditworthiness to default risk. Default occurs when realized repayment capacity falls below a fixed threshold, and tighter underwriting raises the creditworthiness cutoff for approval and therefore lowers the average default probability among originated loans. Around the steady state, a local approximation of this relationship gives the exponential schedule in equation (30). Appendix F provides the exact portfolio-default expression and the derivation.

I calibrate the slope of the schedule using loan-level performance data and the same applicant-quality index used in the approval calibration. I match HMDA applications to GSE loan performance

[28]The cutoff $\hat{q}_g$ therefore summarizes a lender's approval policy using the common applicant-quality index $x$. Although it does not capture all information used in actual approval decisions, it provides a measure that is comparable across banks and NBFIs.

data and estimate the relationship between borrower quality and subsequent default separately for banks and NBFIs. Appendix G shows the details of the procedure for estimating $\delta_{1,j}$.

I then choose $\delta_{0,j}$ so that the default schedule matches the observed sectoral default rate at $q_j$. The annual default rates are 1.76 percent for banks and 4.51 percent for NBFIs, based on GSE loans matched to HMDA applications. I convert these rates to quarterly rates and use them as the calibration targets to match the frequency of the model.

**Screening Cost and Effective Default Loss Retention** Screening uses real resources, and its cost is assumed to increase with underwriting stringency according to

$$s_j(q) = c_j \exp(q).$$

I use the exponential form instead of the quadratic screening cost used in Dell'Ariccia et al. (2014). The reasons are twofold. First, the underwriting index $q$ is measured using a standardized principal component and can take both positive and negative values. Under a quadratic specification, moving $q$ further below zero raises screening costs even though underwriting becomes less stringent. This is not consistent with the idea that less screening requires fewer resources. Second, because $q$ is measured using a principal component, its origin is a normalization. Under the exponential specification, a shift in the origin of $q$ is absorbed by $c_j$ without changing the shape of the function.

Given the calibrated approval and default schedules, I jointly calibrate the screening cost parameter $c_j$ and the effective default loss retention parameter $\kappa_j$ from the lender's pricing and underwriting conditions. More specifically, I choose $c_j$ and $\kappa_j$ so that both conditions hold at the observed steady state, given the calibrated approval and default schedules.[29] Internally calibrated parameters are summarized in Table 2.

# 6. Steady-State Effects of Tighter Bank Capital Requirements

Using the calibrated model, I examine how the economy and aggregate default risk change as capital requirements are tightened to varying degrees in the steady state. I recompute the steady-state equilibrium for alternative values of the bank capital requirement $\nu$, holding all other parameters at their calibrated values. The analysis is useful in that it shows through which channels and to

[29]The recovered values of $\kappa_j$ satisfy $\kappa_B > \kappa_{NB}$. While these values are model-implied parameters conditional on the steady-state targets, the recovered ordering is consistent with the difference in default loss internalization between banks and NBFIs discussed in Section 3.4. I additionally show that interest rates increase less steeply with observable borrower risk for NBFIs than for banks, while the probability of default increases more steeply using GSE data in Appendix G.4. Thus, the weaker pricing response of NBFIs is accompanied by a stronger deterioration in realized loan performance, rather than a smaller increase in default risk.

**Table 2.** Internally Calibrated Parameter Values

| Parameter | Value | Description | Target or Source |
|---|---|---|---|
| *Panel A. Approval schedule* | | | |
| $b_{0,B}$ | 0.2410 | Bank approval-schedule level | $p_B(q_B) = 0.8013$ |
| $b_{0,NB}$ | 0.1311 | NBFI approval-schedule level | $p_{NB}(q_{NB}) = 0.8809$ |
| $b_{1,B}$ | 0.0936 | Bank approval-schedule slope | Estimation, See Text |
| $b_{1,NB}$ | 0.1407 | NBFI approval-schedule slope | Estimation, See Text |
| *Panel B. Default schedule* | | | |
| $\delta_{0,B}$ | 0.0045 | Bank default-schedule level | $d_B(q_B) = 1.76\%$ annually |
| $\delta_{0,NB}$ | 0.0116 | NBFI default-schedule level | $d_{NB}(q_{NB}) = 4.51\%$ annually |
| $\delta_{1,B}$ | 0.0806 | Bank default-schedule slope | Estimation, See Text |
| $\delta_{1,NB}$ | 0.1353 | NBFI default-schedule slope | Estimation, See Text |
| *Panel C. Verification costs and effective default loss retention* | | | |
| $c_B$ | 0.0002 | Bank verification-cost | Bank FOCs, equations (12) and (13) |
| $\kappa_B$ | 0.9079 | Bank effective default loss retention | Bank FOCs, equations (12) and (13) |
| $c_{NB}$ | 0.0009 | NBFI verification-cost | NBFI FOCs, equations (17) and (18) |
| $\kappa_{NB}$ | 0.7490 | NBFI effective default loss retention | NBFI FOCs, equations (17) and (18) |

what extent those channels contribute to the changes.

I vary $\nu$ from 6% to 24%, a range consistent with values studied in the literature.[30] The lowest value is the model's benchmark value and corresponds to the Basel III minimum Tier 1 capital requirement, while the upper limit represents a stringent counterfactual suggested in the literature, yielding a narrower range than that considered in Begenau and Landvoigt (2022), with an upper bound of 30%.

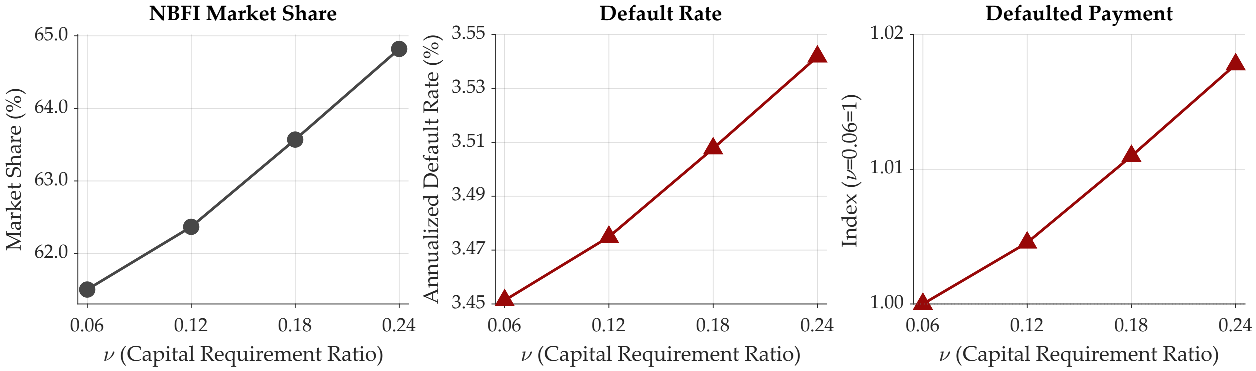
Figure 7 shows the NBFI share of loan originations, the aggregate default rate, and aggregate defaulted payments.

The first panel of Figure 7 shows that the regulation generates leakage from banks to NBFIs, consistent with the model in Buchak et al. (2018) and Begenau and Landvoigt (2022). The NBFI share of loan originations rises from 61.5% to 64.82%, an increase of 3.32 percentage points. In my model, this reallocation occurs because a tighter capital requirement raises the cost of bank lending and induces banks to apply stricter underwriting standards with higher loan rates. Therefore, given their application preferences, NBFI offers become more attractive, and some borrowers instead apply to NBFIs, whose more permissive underwriting standards allow a larger fraction of them to obtain credit.

The remaining two panels show the effect of tighter capital regulation on credit risk, which I decompose in greater detail in Section 6.1. The middle panel shows that the aggregate default

[30] Quantitative studies report a wide range of optimal risk-weighted bank capital ratios, including 16–20% in Miles et al. (2013), 15–23% in Dagher et al. (2016), 13–26% in Firestone et al. (2019), and 16–31%, with a baseline estimate of approximately 23%, in Soederhuizen et al. (2023). Pancost and Robatto (2023) obtain 21.9% in their baseline model and values up to 24.5% in extensions.

**Figure 7.** Intermediation response to higher bank capital requirements




**Notes.** Each point is computed by re-solving the steady-state equilibrium at the indicated value of $\nu$, holding all other parameters at their benchmark values.

rate rises from 3.45% to 3.54% as $\nu$ increases from 6% to 24%. Banks improve the quality of the loans remaining on their balance sheets by tightening their underwriting standards. However, this improvement is more than offset by the reallocation of borrowers toward NBFIs, where more permissive underwriting allows riskier marginal borrowers to obtain credit. The 9-basis-point increase in the aggregate default rate is comparable to credit-risk responses in related quantitative models of bank capital regulation.[31] More importantly, this channel becomes more consequential following the financial stress shock described in Section 7.

The right panel shows the change in aggregate defaulted payments. I normalize aggregate defaulted payments to one at $\nu = 0.06$, measuring changes relative to the benchmark while incorporating the endogenous response of aggregate credit volume.[32] The index rises from 1 to 1.0178 as $\nu$ increases from 0.06 to 0.24, indicating a 1.78% increase in aggregate defaulted payments. Total credit contracts, as will be shown in Section 6.1, because NBFI loans are imperfect substitutes for bank loans and borrowers who migrate across sectors recover only part of the credit withdrawn by banks. Nevertheless, the increase in credit risk due to looser NBFI underwriting standards, which allow riskier borrowers who would otherwise remain unfunded to obtain credit, dominates the reduction in credit volume.

## 6.1. Decomposition of the Effect of Regulation on Total Defaults

This section decomposes and quantifies the underlying channels through which total defaults respond to tighter bank capital requirements. Define $\pi_{NB}$ as the NBFI share of aggregate *originations*.

[31] Linearly rescaling the changes reported in Dempsey (2025) and Begenau and Landvoigt (2022) to an 18-percentage-point increase in capital requirements yields approximately 4.2 basis points for bank C&I loan charge-offs and 9.2 basis points for shadow-bank defaults, respectively.

[32] At this benchmark, quarterly aggregate defaulted payments amount to 0.41% of quarterly output.

Its relation to the application share $\omega_{NB}$ is expressed in odds form as

$$\frac{\pi_{NB}}{1-\pi_{NB}} = \frac{\omega_{NB}}{1-\omega_{NB}} \frac{p_{NB}(q_{NB})}{p_B(q_B)}. \tag{31}$$

Given the definitions of $\pi_{NB}$ and $\pi_B = 1 - \pi_{NB}$, the origination-weighted aggregate default rate is

$$d^{\text{agg}} = \pi_{NB} d_{NB}(q_{NB}) + (1-\pi_{NB}) d_B(q_B), \tag{32}$$

and total defaulted principal can then be written as

$$\mathcal{D} = d_{NB}(q_{NB}) L_{NB} + d_B(q_B) L_B = L \times [\pi_{NB} d_{NB}(q_{NB}) + (1-\pi_{NB}) d_B(q_B)] = L \times d^{\text{agg}}. \tag{33}$$

I then take the total derivative of $\mathcal{D}$ with respect to $\nu$ and decompose the resulting expression to derive the condition under which tighter capital regulation increases the total defaulted principal. Proposition 2 presents this condition.

Proposition 2. *Suppose tighter capital regulation raises bank underwriting stringency, so that* $\mathrm{d}q_B/\mathrm{d}\nu > 0$, *and reduces aggregate lending, so that* $\mathrm{d}L/\mathrm{d}\nu < 0$. *Then* $\mathrm{d}\mathcal{D}/\mathrm{d}\nu > 0$ *if and only if*

$$\underbrace{L\pi_{NB}(1-\pi_{NB})\left[d_{NB}(q_{NB}) - d_B(q_B)\right]\mathcal{S}}_{\textit{Origination reallocation}} + \underbrace{L\pi_{NB} d'_{NB}(q_{NB})\frac{\mathrm{d}q_{NB}}{\mathrm{d}\nu}}_{\textit{Within-NBFI underwriting}} > \underbrace{L(1-\pi_{NB})\left[-d'_B(q_B)\right]\frac{\mathrm{d}q_B}{\mathrm{d}\nu}}_{\textit{Within-bank improvement}} + \underbrace{d^{\text{agg}}\left[-\frac{\mathrm{d}L}{\mathrm{d}\nu}\right]}_{\textit{Aggregate lending}}. \tag{34}$$

*where* $\mathcal{S} \equiv \varphi\left(\frac{\mathrm{d}\log R^{\ell}_B}{\mathrm{d}\nu} - \frac{\mathrm{d}\log R^{\ell}_{NB}}{\mathrm{d}\nu}\right) + \eta\left(\frac{\mathrm{d}\log p_{NB}(q_{NB})}{\mathrm{d}\nu} - \frac{\mathrm{d}\log p_B(q_B)}{\mathrm{d}\nu}\right) + \left(\frac{\mathrm{d}\log p_{NB}(q_{NB})}{\mathrm{d}\nu} - \frac{\mathrm{d}\log p_B(q_B)}{\mathrm{d}\nu}\right)$

Proof. See Appendix D.2. □

The proposition shows that an increase in the aggregate default rate does not necessarily translate into an equally large increase in total defaults. More specifically, the reallocation of applications toward NBFIs with looser screening standards, together with each sector's underwriting responses, determines the change in $d^{\text{agg}}$, while the response of aggregate originated lending determines the amount of credit to which this default rate applies.

Table 3 reports the contribution of each channel to the increase in aggregate defaulted payments in Panel A and how each key variable responds to changes in capital regulation in Panel B. Each value is evaluated at $\nu = 0.06$.

Panel A shows that the origination reallocation channel dominates the other channels, including the reduction made in aggregate lending volume. This is mainly driven by $\mathcal{S}$, which is quantitatively large enough to dominate other effects. However, the direct effects of changes

**Table 3.** Four-Channel Decomposition of the Total Defaulted Principal Response

| **Panel A. Channel contributions (bps)** | | **Panel B. Equilibrium objects** | |
|---|---|---|---|
| **Channel** | **Contribution** | **Object** | **Value** |
| 1. Origination reallocation | 5.0848 | Reallocation strength $\mathcal{S}$ | 0.3124 |
| 2. Within-NBFI underwriting | 0.0004 | NBFI underwriting response $\mathrm{d}q_{NB}/\mathrm{d}\nu$ | −0.0001 |
| 3. Within-bank underwriting | −0.0611 | Bank underwriting response $\mathrm{d}q_B/\mathrm{d}\nu$ | 0.0448 |
| 4. Aggregate lending volume | −3.3782 | Aggregate lending response $\mathrm{d}L/\mathrm{d}\nu$ | −0.0061 |
| Total | 1.6458 | | |

Notes. $\omega_{NB}$ denotes the NBFI application share and $\pi_{NB}$ denotes the NBFI origination share. Channel contributions in Panel A are basis points of benchmark aggregate originated lending per unit change in $\nu$. The four contributions sum to the response of total defaulted principal normalized by benchmark aggregate lending.

in underwriting standards are relatively small. Bank underwriting responds to tighter capital requirements, with $\mathrm{d}q_B/\mathrm{d}\nu = 0.045$, but the resulting reduction in the bank default rate contributes only −0.061 basis points. This is because changes in underwriting standards do not translate into a large reduction in bank default rates due to the low semi-elasticity of the default rate with respect to lending standards, $\delta_{1,B}$. The same logic applies to NBFIs. NBFI underwriting responds indirectly through the endogenous funding rate $R^F$. This is because, as tighter capital regulation is imposed, funding sources also migrate from deposits to money market funds as bank balance sheets shrink and more money market funds are supplied. Then $R^F$ decreases, and therefore $q_{NB}$ decreases due to Proposition 1, but the resulting change in $q_{NB}$ is limited and does not generate a large change in either approval or default rates. Finally, the aggregate lending volume declines because bank loans and NBFI loans are imperfect substitutes, and the rise in the bank loan rate results in lower aggregate lending volume.

## 6.2. Sensitivity Analysis and Extension

I briefly outline the sensitivity analyses and model extensions in this section.

**Sensitivity Analysis.** I conduct a sensitivity analysis by varying five key sets of parameters, including (1) the elasticity of substitution with respect to loan rates ($\varphi$), (2) the approval elasticity ($\eta$), (3) the share of bank applications ($\psi_B$), and (4) the default schedule parameters ($\delta_{1,B}$ and $\delta_{1,NB}$) and (5) the default schedule parameters ($b_{1,B}$ and $b_{1,NB}$). While I vary the parameter values over a wide range of possible values, the effects of regulation on the default rate and defaulted payments remain quantitatively stable. The corresponding results are presented in Appendix H.1.

**Extension.** I relax key assumptions of the model to reflect the key margins. First, I relax the assumption of independence between creditworthiness and the application friction shock and allow for heterogeneous borrower types with different elasticities of substitution with respect to loan rates and approval rates. In the extension, risky borrowers exhibit exogenously higher default rates and are more responsive to changes in loan rates and approval rates than safe borrowers. Second, I allow banks to fund NBFIs and NBFIs to borrow from banks, in the spirit of Acharya et al. (2024) and Xu (2025). Third, I allow banks to sell their loans, comparing the benefit of relaxing the regulatory constraint with the secondary-market selling cost. Lastly, I allow applicants rejected by banks to reapply to NBFIs after paying a search cost, as highlighted in Agarwal et al. (2024). The first two extensions strengthen the effect of regulation on default measures, whereas the last two mitigate this effect but preserve the results on the effect of tighter capital regulation on the default rate and defaulted payments. The details of the extension and results are presented in Appendix H.2.

# 7. Financial Stress Experiment

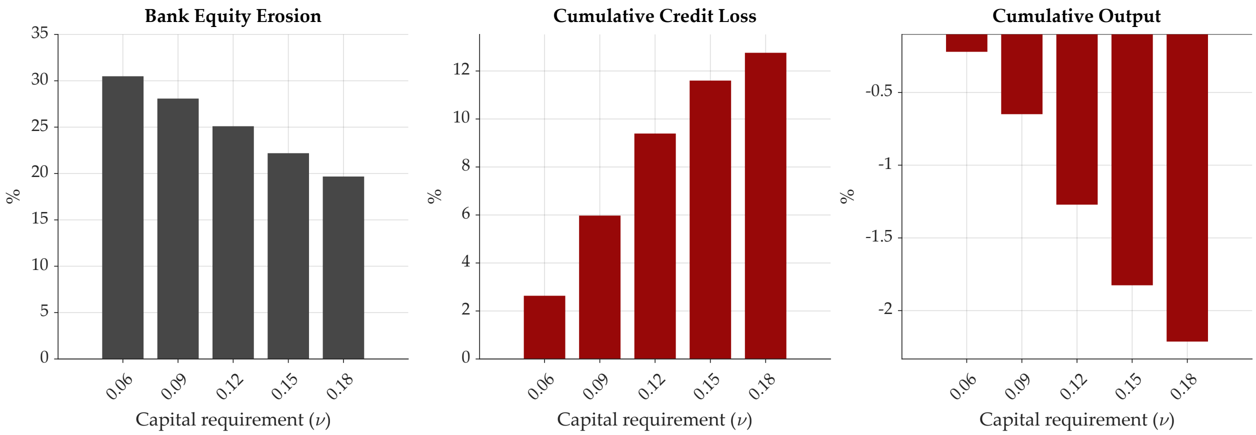
I use the calibrated model to examine how the economy responds to financial stress when bank capital regulation is tighter. The objective of the regulation is to make banks sufficiently resilient to absorb adverse shocks. In this experiment, I examine whether it achieves this objective and what happens to credit losses and economic activity after the shock. At each capital requirement, I solve for the steady state, holding the calibrated parameters fixed, and log-linearize the equilibrium conditions around that steady state.

To implement the experiment, I reduce the value of outstanding loans held by banks and NBFIs by 5%. This experiment is similar in spirit to the capital-quality shock in Gertler and Karadi (2011), which lowers the quality of assets held by financial intermediaries. The proportional loss is the same for both sectors and at each level of capital regulation. Once the value of loans falls, the equity of the intermediaries declines.

Figure 8 reports bank equity erosion on impact and the cumulative responses of credit losses, measured as defaulted principal, and output over the first sixteen quarters following an initial 5% decline in the value of loans held by banks and NBFIs.

The left panel shows that bank equity erodes less as capital regulation becomes tighter. As capital regulation tightens, banks enter the shock with lower leverage, holding fewer loans relative to their equity, so the same proportional loss on loans causes a smaller decline in equity. However, credit losses increase more, as shown in the middle panel. The cumulative response rises from 2.17 when the capital requirement is 6% to 10.51 when it is 18%. The right panel shows that the cumulative output response also becomes more negative, changing from −0.18% to −1.82%. Tighter regulation therefore reduces the damage to bank equity, but the economy experiences greater credit losses and a larger decline in output.

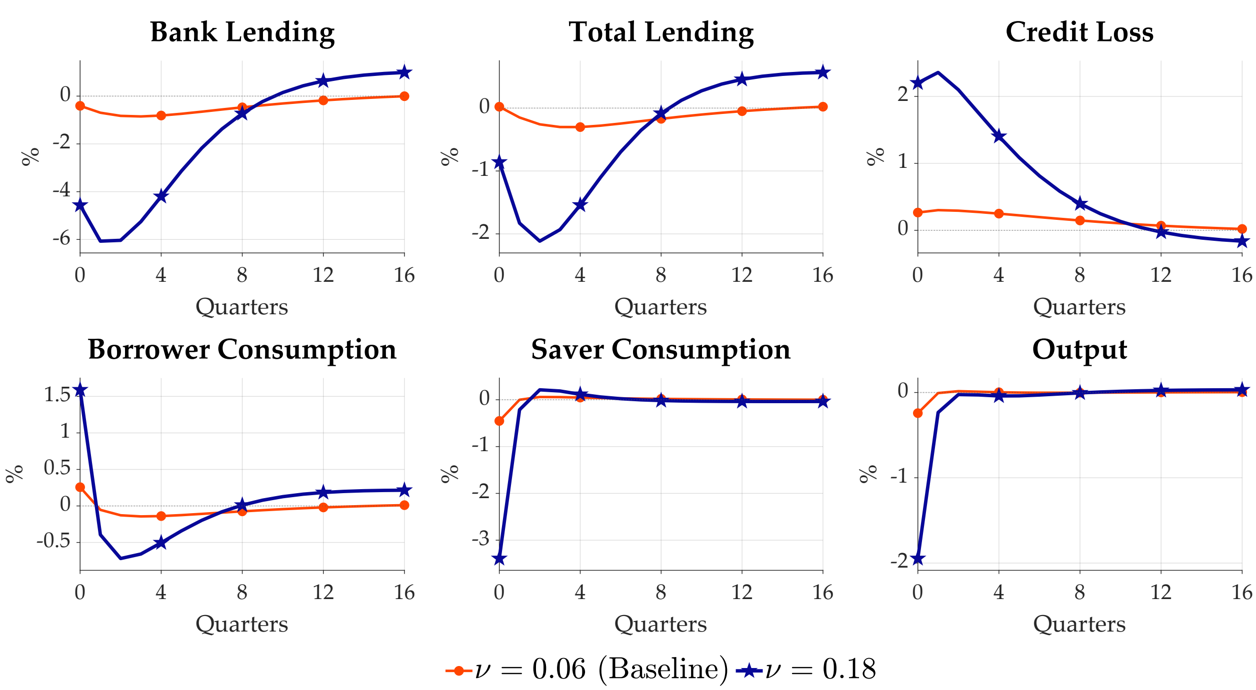
**FIGURE 8.** Financial Stress Outcomes across Bank Capital Requirements




**Notes.** Each economy faces the same proportional loss on bank and NBFI loans. The left panel reports the magnitude of the decline in bank equity on impact, as a percentage of its steady-state value. The middle and right panels report the sums of quarterly percentage deviations (cumulative IRFs) of aggregate defaulted principal and output from the steady states over 16 quarters after the shock.

**Unpacking the Results** Figure 9 shows the impulse responses behind these results. The top row reports bank equity, NBFI equity, and credit losses. The bottom row reports borrower consumption, saver consumption, and output.

**FIGURE 9.** Impulse Responses to Financial Stress




**Notes.** The top row reports bank lending, total lending, and aggregate defaulted principal ($d^{agg}L$). The bottom row reports borrower consumption ($C_B$), saver consumption ($C_S$), and output ($Y$). Responses are percentage deviations from each steady state.

Bank lending contracts more sharply under tighter capital regulation. The total lending response also becomes more negative in the early quarters. The third panel shows that credit losses rise more under tighter regulation. To understand why, consider what happens to lending after banks lose equity. Although banks lose a smaller fraction of their equity, their thinner buffers above the regulatory requirement leave them less room to maintain lending. Some borrowers instead apply to NBFIs and obtain credit under their looser standards. NBFIs also lose equity, but they do not face the bank capital requirement and can raise additional funding to continue lending. Banks therefore reduce lending and rebuild equity while NBFIs provide more credit.

The bottom row shows the effects of the shock on households and output under different regimes. Borrower consumption rises at first because the amount they repay declines. However, as less additional borrowing becomes available, consumption then falls below the steady state. For savers, defaults represent a loss, and these losses affect how much savers can consume. The middle panel shows that saver consumption falls more sharply on impact when regulation is tighter. Output also falls more as aggregate labor declines. Although output subsequently recovers, the recovery does not offset the larger initial contraction.

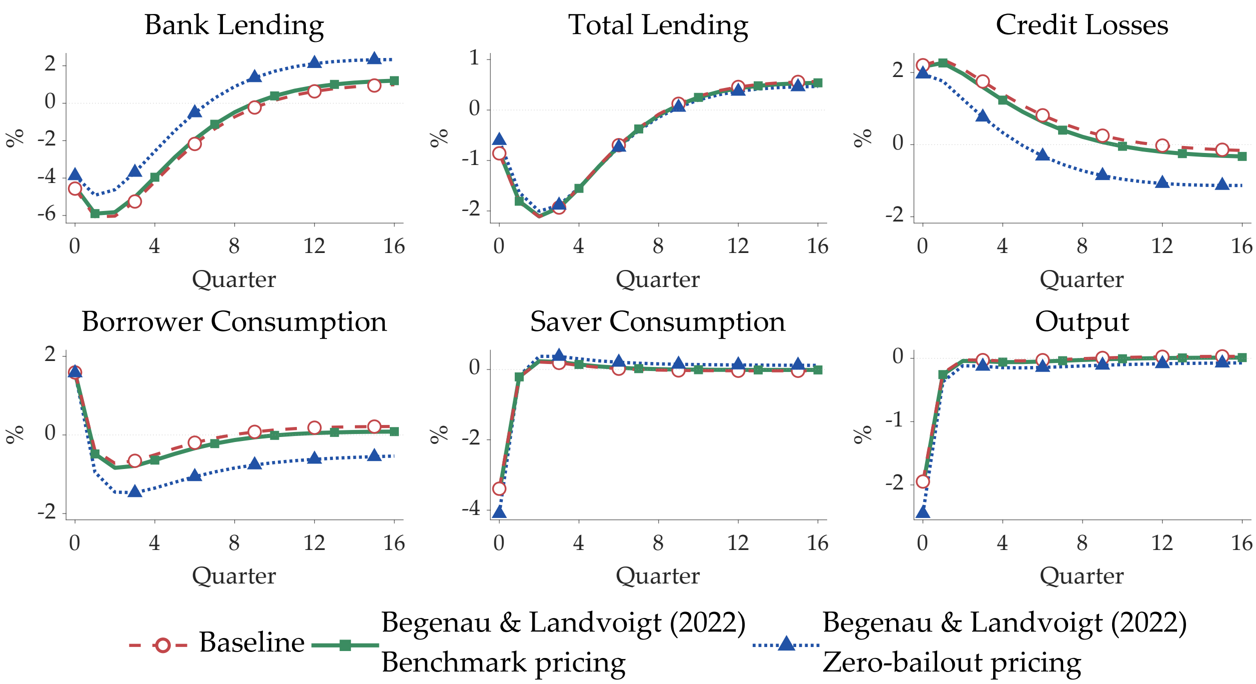
The results show that capital regulation can achieve its objective when I focus on banks. Their equity erodes less after the shock. However, aggregate credit losses increase, and the consumption and output responses show why bank resilience alone is insufficient to evaluate how the economy recovers from financial stress.

**Funding Risks for NBFIs** In the baseline model, NBFIs can obtain funding from money market funds even when they experience severe equity erosion. In practice, investors require a higher rate of return to provide funding to riskier NBFIs. I incorporate this consideration by introducing a funding risk premium that increases with NBFI leverage into the money market funding rate, $R_t^F$. The benchmark coefficient, $\chi_F = 0.0012$, is calibrated using the debt-pricing relationship in Begenau and Landvoigt (2022). I also consider a stronger response, $\chi_F = 0.0082$, calibrated from the debt-pricing relationship in Begenau and Landvoigt (2022) with the bailout probability set to zero, evaluated at the benchmark state.

Figure 10 shows how NBFI funding risk changes the responses to financial stress under tighter capital regulation. NBFIs now pass higher funding costs on to borrowers, raising loan rates and borrowers rely less on NBFI loans. Then, the credit loss response is smaller and declines more rapidly, particularly under zero-bailout pricing assumption. However, borrower consumption falls more sharply after its initial increase, and saver consumption falls more on impact. The contraction in output is consequently deeper.

The cumulative responses over the first sixteen quarters show that the ordering across regulatory regimes persists. These responses are calculated by summing quarterly percentage deviations from each economy's own steady state. Raising $\nu$ from 0.06 to 0.18 increases the cumulative

**Figure 10.** Impulse Responses with NBFI Funding Risk




**Notes.** All responses are evaluated at $\nu = 0.18$. Red dashed lines report the baseline model without the funding risk premium. Green solid lines and blue dotted lines report the funding-risk specifications based on benchmark pricing and zero-bailout pricing, respectively, using the debt-pricing relationship in Begenau and Landvoigt (2022). The top row reports bank lending, total lending, and aggregate defaulted principal. The bottom row reports borrower consumption, saver consumption, and output. Responses are percentage deviations from each economy's own steady state.

credit-loss response from 2.63 to 12.76 in the baseline model, from 0.17 to 10.23 under benchmark funding-risk pricing, and from −12.58 to −2.84 under zero-bailout pricing. The corresponding increases are 10.12, 10.06, and 9.75, respectively. Under zero-bailout pricing, tighter regulation therefore produces a smaller cumulative decline in credit losses.

The cumulative output response falls from −0.22 to −2.21 in the baseline model, from −0.55 to −2.59 under benchmark funding-risk pricing, and from −2.12 to −4.38 under zero-bailout pricing. The corresponding additional declines are 1.99, 2.04, and 2.26, respectively. Thus, although NBFI funding risk reduces the cumulative credit-loss response within each regulatory regime, tighter bank capital regulation continues to generate a higher credit-loss response and a deeper output contraction.

**Do We Need to Abolish Capital Regulation?** While the model shows that tighter capital regulation leads to larger credit losses and a deeper output decline, this does not imply that capital regulation should be at 0% or abolished. The model omits an important benefit of preserving bank capital, which is the reduction in expected financial crisis costs as highlighted in Begenau and Landvoigt (2022) and Dempsey (2025). A back-of-the-envelope calculation that incorporates this benefit supports retaining a positive capital requirement. However, the credit losses associated with tighter regulation offset part of this benefit. Details of this calculation are provided in Appendix I.

# 8. Policy Implication: Regulating NBFI Underwriting

The main force increasing aggregate credit risk, measured by default rates and default payments, is the reallocation of applications toward NBFIs as bank credit becomes less attractive due to higher loan rates and lower approval probabilities. This channel is weak, however, when the NBFI market share, $\omega_{NB}$, is close to either zero or one, or when the default-rate gap between NBFIs and banks, $d_{NB} - d_B$, is small. In these cases, the increase in risk due to borrower migration may be outweighed by the benefits associated with safer bank lending.

As Proposition 2 shows, this reallocation affects the risk composition of credit only when NBFIs apply less stringent underwriting standards and consequently originate loans with higher default rates. If the two sectors originated loans with similar default risk for otherwise comparable borrowers, regulation would mainly shift credit provision across intermediary types rather than materially change the risk of newly originated loans.

This mechanism motivates a complementary underwriting requirement for NBFIs aimed at limiting the resulting deterioration in the risk composition of credit.

## 8.1. Regulating NBFI Underwriting

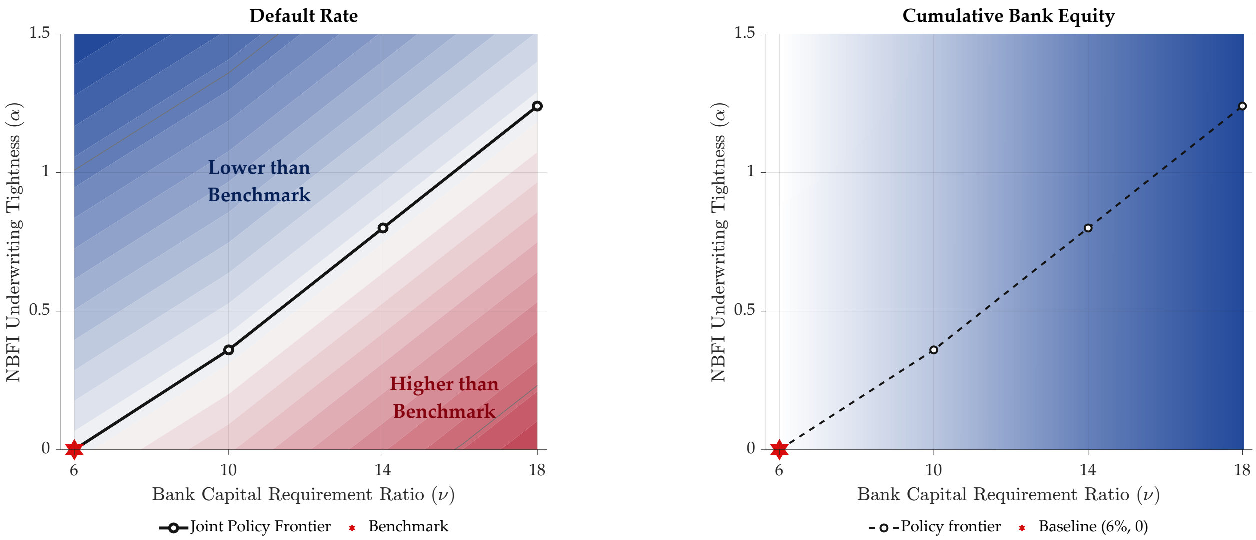
Let $\alpha_q \geq 0$ denote the fraction of the baseline bank–NBFI gap in underwriting stringency $q$ closed by the requirement.

$$\begin{aligned} q_{NB}^{\text{reg}}(\alpha_q) &= q_{NB} + \alpha_q\,(q_B - q_{NB}) \\ &= (1-\alpha_q)q_{NB} + \alpha_q q_B, \end{aligned} \tag{35}$$

Here, $q_B$ and $q_{NB}$ denote their steady-state levels when the capital requirement is $\nu = 0.06$. When $\alpha_q = 0$, the NBFI chooses $q_{NB}$ from its own first-order condition. When $\alpha_q > 0$, the requirement replaces that condition and fixes $q_{NB}$ at the regulated steady-state target throughout the stress response.

The policy target in this exercise is the payment-weighted default rate over the first sixteen quarters after the stress shock. Let $\ell(\nu, \alpha_q)$ denote this default rate for each level of $\nu$ and $\alpha_q$ under the financial stress scenario in Section 7. I then search for the minimum level of $\alpha_q$, representing an intervention in NBFI underwriting stringency, required to keep this default rate at or below its value in the baseline economy, where $\nu = 0.06$ and $\alpha_q = 0$. A value of $\alpha_q$ greater than 1 implies

**FIGURE 11.** Joint Bank Capital and NBFI Underwriting Policies: Default Rate and Bank Equity




**Notes.** The horizontal axis reports the bank capital requirement, $\nu$, and the vertical axis reports the fraction of the baseline bank–NBFI underwriting gap closed by the policy, $\alpha_q$. The left panel reports the default rate over the first sixteen quarters after the stress shock, weighted by scheduled loan repayments and normalized by its baseline value. Blue indicates a default rate below the baseline, while red indicates a default rate above it. The right panel reports the difference between each policy combination and the baseline in the sum of quarterly bank equity percentage deviations from their respective steady states over the first four quarters following the stress shock, measured in percentage-point-quarters. Positive values (blue) indicate less cumulative equity erosion than in the baseline, while negative values (red) indicate greater erosion. The red star marks the baseline economy, $(\nu, \alpha_q) = (0.06, 0)$. In both panels, black markers identify the minimum solved-grid $\alpha_q$ at each $\nu$ that keeps the default at or below its baseline level.

that the underwriting standard imposed on NBFIs is stricter than that of banks.

$$\alpha_q^{\text{req}}(\nu) \equiv \min \left\{ \alpha_q \geq 0 : \ell(\nu, \alpha_q) \leq \ell(0.06, 0) \right\}. \tag{36}$$

Figure 11 plots the sixteen-quarter default rate relative to its value when $\nu = 0.06$ without intervention. The blue region captures policy mixes that lower this default rate compared to the baseline, while the red region reports higher default rates. The black line reports the minimum $\alpha_q$ required at a given level of $\nu$ to keep this default rate at or below the baseline level. The required adjustment rises with the bank capital requirement. On the solved grid, closing 36% of the baseline underwriting gap is needed at a 10% bank capital requirement. The corresponding values are 80% at a 14% requirement and 124% at an 18% requirement. The larger adjustment reflects the greater migration of lending toward NBFIs as bank capital regulation tightens.

Along the default-rate frontier, the right panel shows that the cumulative bank equity response improves relative to the baseline as the bank capital requirement increases, while this improvement remains almost unchanged as NBFI underwriting is tightened. In particular, under the policy mix with $\nu = 0.18$ and $\alpha_q = 1.24$, cumulative bank equity erosion is reduced by 44.94 percentage-point-quarters relative to the baseline, which is almost the same as the reduction achieved when there is no NBFI underwriting intervention. Therefore, the two policies are complementary in that tighter NBFI underwriting lowers the default rate while largely preserving the reduction in cumulative bank equity erosion generated by tighter bank capital regulation.

# 9. Capital Regualtion, Securiziation, and Credit Risk

I analyze mortgage market data, where detailed application-level and loan-performance information allows me to study how lending decisions differ across banks and NBFIs and how these differences shape the realization of credit risk. The mortgage setting, however, raises three questions for interpreting the empirical and quantitative results. First, if mortgages can be sold through secondary markets, why do bank capital requirements affect mortgage origination in the first place? Second, could the observed retreat of banks and expansion of NBFIs reflect other post-crisis forces, such as litigation exposure or changes in the capital treatment of mortgage servicing rights, rather than banks' capital constraints? Third, if originated loans are subsequently securitized or transferred to government-related institutions, why should an increase in aggregate credit risk remain economically relevant? The following subsections address these three questions in turn.

## 9.1. Why Do Capital Requirements Affect Bank Mortgage Lending Despite Securitization?

Although selling or securitizing mortgages can reduce banks' exposure to capital requirements by replacing loans with assets carrying lower risk weights, securitization does not eliminate the relevance of capital requirements for banks' mortgage lending for three reasons.

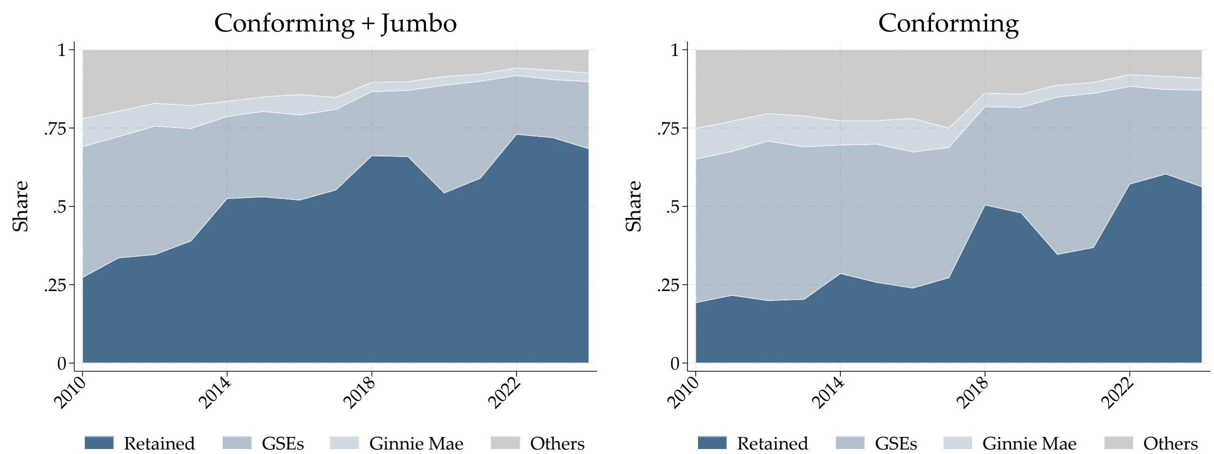
First, selling the underlying loans does not necessarily eliminate the capital requirement exposure associated with mortgage origination. The assets that banks receive after selling the loans, such as mortgage-backed securities, are also subject to capital requirements, although they carry lower risk weights. In addition, while selling loans removes the underlying loans from the balance sheet, banks commonly retain mortgage servicing rights (MSRs) after selling the loans (Hamdi et al. 2023; Zheng 2024). MSRs represent the asset value of the right to service mortgage loans, including collecting principal and interest payments from borrowers and transferring them to investors, after the originating banks sell the loans to third parties. Importantly, these assets are subject to relatively high risk weights under capital regulation.[33] In other words, mortgage

[33] MSRs are the rights to collect mortgage payments and provide other servicing functions in exchange for servicing fees. Capital rules require banks to deduct part of their MSRs from common equity tier 1 capital, while the remaining portion is subject to a 250 percent risk weight. See 12 C.F.R. § 217.22(d) and § 217.32(l)(4).

origination remains relevant to capital requirements even when the underlying loans are sold, because banks can remain exposed through the assets and servicing rights associated with those loans.

Second, in practice, mortgages that are eligible for sale to third parties still remain on bank balance sheets. Figure 12 shows that a non-negligible share of loans are still retained on the bank balance sheet.

**Figure 12.** Bank Retention Rate




**Note.** This figure shows the disposition of mortgage loans originated by banks from 2010 to 2024 using HMDA data. Loans are classified based on the HMDA loan purchaser code into four categories. "Retained" includes loans that are not reported as sold to these entities and remain with the originating bank. "Bank to GSE" includes loans sold to Freddie Mac and Fannie Mae, while "Bank to Ginnie Mae" includes loans sold through Ginnie Mae. "Others" captures the case where the loans are sold to other institutions. The left panel reports the shares for all mortgage originations, while the right panel restricts the sample to conforming loans. *Source.* HMDA

Since 2018, banks have retained around 30–60% of loans that are sellable (i.e., conforming loans), and this share rises to 50–70% when including loans that are not eligible for sale (i.e., jumbo loans). These retained loans remain subject to risk-based capital requirements.[34] Importantly, selling loans is not a costless way to avoid capital requirements. Fuster et al. (2013) emphasize that the originating lender remains exposed to put-back risk. A delinquency may prompt a review of the loan file, and the lender may be required to repurchase the loan if the GSE identifies a violation of its underwriting or eligibility representations and warranties. They also argue that a larger cost may arise from the additional underwriting and legal resources used to prevent or contest repurchase claims. Therefore, banks face a trade-off between retaining loans that are subject to

[34] Qualifying first-lien residential mortgages generally receive a 50 percent risk weight, while other first- and junior-lien mortgages receive a 100 percent risk weight. See 12 C.F.R. §217.32(g). Even mortgages intended for sale remain subject to capital requirements while they are held on the bank's balance sheet before sale. See 12 C.F.R. §§217.31(a), 217.32(g).

capital requirements and selling them at a cost. The substantial retention rate in Figure 12 shows that mortgage origination remains exposed to bank capital regulation even when loans are eligible for sale.

Lastly, even for mortgages that are ultimately sold, there is pipeline risk between origination and sale because the loans are held on banks' balance sheets during this period and are therefore relevant to capital regulation, as highlighted by Kim et al. (2022). Capital requirements can therefore affect banks' origination incentives during the period in which loans remain on their balance sheets.

Therefore, securitization does not eliminate the relevance of capital requirements for banks' mortgage lending decisions. It is noteworthy that the results showing the association between capital regulation and credit allocation to riskier borrowers, as well as higher default rates, are based on GSE loans. This evidence is consistent with capital regulation affecting mortgage lending even for loans that are ultimately sold. Nevertheless, securitization can mitigate the relevance of capital regulation for bank lending, and I explicitly incorporate this margin in an extension of the model in Section 6.2.

## 9.2. Could Other Mortgage Market Factors Drive the Results?

Other post-crisis forces may also have contributed to the decline in bank mortgage lending and the expansion of NBFIs. Frame et al. (2026) highlight that large banks faced substantial litigation exposure following the financial crisis, which may have reduced their lending. The Basel III revisions also tightened the capital treatment of servicing assets, and this provides another channel through which capital regulation could affect mortgage lending, as Buchak et al. (2018) and Benson et al. (2026) highlight. Although the revision to MSRs is itself part of the effect of capital requirements and provides a channel through which the concern about securitization discussed above can be addressed, the results could still be interpreted as being driven mainly by the MSR rule change rather than by how well capitalized banks were to begin with. In other words, the question is whether the estimated effect reflects the capital charge associated with servicing rights alone or the bank's overall capital position, and this distinction matters for the modeling choice.

To address concerns that the increase in NBFI lending may reflect other post-crisis changes affecting banks, I conduct two exercises. I first change the treatment from the market share of regulated banks to the regional-level capital ratio of regulated banks. In other words, within each region, I replace the treatment variable with the capital ratios of regulated banks, aggregated to the regional level using their market shares as weights, which captures banks' initial capitalization. Then, I augment the specification with exposures to mortgage-related legal overhang and exposure to the MSR rule change, as I do in the baseline. When these exposures are included jointly, counties more exposed to weakly capitalized banks experience a larger increase in the NBFI origination share after 2013. Appendix C.4 provides the construction of these measures, the specification, and the event-study results.

Second, I conduct a bank-level analysis using variation within regulated banks. I restrict the sample to banks that are subject to stress tests and use variation in capital ratios, MSR exposure measured as MSR holdings relative to equity, legal overhang, and stress capital buffers, which are proxied by projected stress losses relative to assets. By doing so, I can examine to what extent each exposure can explain the reduction in originations by each bank, and I show that the capital ratio can explain the reduction in originations along with the MSR holdings relative to equity. Appendix C.5 provides the details on the regression and the results.

## 9.3. Why Does Credit Risk Matter If Loans are Securitized?

From the policymakers' perspective, securitization changes who bears credit losses but does not eliminate the losses associated with credit risk. In particular, transferring credit risk to government-related institutions such as the GSEs does not necessarily make an increase in aggregate credit risk less relevant. This was evident during the COVID-19 period, when mortgage delinquency required public measures to support the functioning of the securitization system, ultimately relying on public resources and taxpayer support. The experience of the financial crisis also illustrates this point, as Fannie Mae and Freddie Mac incurred large losses and were ultimately placed into conservatorship with government support. What matters is aggregate credit risk itself rather than the institution that ultimately bears the losses. More fundamentally, defaults generate real resource costs through foreclosure, legal resolution, and property disposition, which arise regardless of which institution ultimately holds the mortgage.

From the banks' perspective, selling loans also does not fully disconnect their exposure from the performance of the loans they eventually sell. Banks can still remain exposed after selling the loans. One important channel is mortgage servicing rights. When default occurs, servicing becomes more costly because banks need to manage delinquent loans and maintain payment flows. Banks can also face putback risk. Poor loan performance can trigger underwriting reviews and require banks to repurchase the loans eventually.

Because capital requirements are intended to make credit intermediation more resilient to adverse shocks, bank equity is only one dimension of this objective. Securitization itself therefore cannot mitigate or trivialize a possible increase in credit risk, especially if that increase is generated by the regulation. Importantly, this margin is also a current concern of regulators. Financial Stability Oversight Council (2025) points out that bank regulation can generate unintended consequences and economic distortions, noting that increased regulatory costs have shifted credit origination from banks toward NBFIs.[35]

## 10. Conclusion

This paper studies how tighter bank capital requirements affect aggregate credit risk when credit intermediation migrates from regulated banks to NBFIs following tighter capital requirements. Using loan-level evidence from the U.S. residential mortgage market, I first show that NBFIs apply more lenient underwriting standards, which can explain the gap between NBFI loans and bank loans in terms of observable risk and their ex post performance. I further show that tighter bank capital regulation contributes not only to the growth of NBFIs but also to a shift in credit toward riskier borrowers, on average, with higher subsequent default rates.

Then, to suggest a mechanism that can explain the empirical facts and quantify to what extent bank regulation can successfully respond to financial stress shocks, I build a general equilibrium model in which banks and NBFIs jointly choose loan rates and underwriting standards, calibrated to the U.S. mortgage market. The model shows that while tighter bank capital requirements induce banks to tighten their standards, they lead applicants to reallocate a larger share of applications and credit toward NBFIs. As more applicants are now processed under looser lending standards, credit risks that would have remained unfunded now materialize by entering the aggregate loan pool and create additional default risk. The model further shows that tighter regulation can successfully insulate the banking sector from financial stress while it leads to a larger deterioration in NBFI equity with larger credit losses. Banks remain stable as they are less exposed to shocks in the credit market, with an inflow of deposits from money market funds, which actually amplifies the losses and erosion that occur in the NBFI sector.

This paper suggests a complementary underwriting requirement for NBFIs that mitigates these unintended costs that regulation can generate. By narrowing the underwriting stringency gap between the two sectors, the requirement limits the credit risk generated by the shift in lending. Even though applications reallocate to NBFIs, tighter NBFI underwriting offsets the resulting increase in aggregate credit risk. Bank capital requirements and NBFI underwriting regulation therefore serve different purposes and should be treated as complementary instruments.

[35] Financial Stability Oversight Council (2025) states that "Recent experience also suggests that bank regulations can result in unintended consequences and economic distortions. One example of such a distortion in recent years is that as banking regulations have become more complex and costly, the share of credit originated by banks has declined. Lending has been driven out of the banking system, often to nonbank intermediaries."

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# Online Appendix

## Appendix A. Additional Evidence on NBFIs' Origination

### A.1. Oaxaca-Blinder Decomposition

This section provides details on the exercise that decomposes the default gap in Section 2.1. The decomposition divides the differences into two terms that capture (i) differences in the risk distributions of loans originated by NBFIs and banks and (ii) differences in default probabilities conditional on the same observed risk, holding the risk distribution fixed at the NBFI distribution.

Let $R_i$ denote the risk index for loan $i$. I construct $R_i$ as the first principal component of credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio, all of which are known to be strong observable predictors of loan performance. The index is normalized so that higher values correspond to riskier underwriting profiles, lower credit scores and higher LTV and DTI ratios jointly. Then, let $D_i \in \{0,1\}$ indicate whether loan $i$ defaults. For each lender type $j \in \{B, NB\}$, where $B$ denotes banks and $NB$ denotes NBFIs, define

$$F_j(r) = \Pr(R_i \leq r \mid j), \qquad d_j(r) = \mathbb{E}[D_i \mid R_i = r, j].$$

Here, $F_j(r)$ is the distribution of the underwriting risk index for loans originated by lender type $j$, and $d_j(r)$ is the default probability conditional on risk index $r$ and lender type $j$. Finally, the average default rate for lender type $j$, denoted by $\delta_j$, can be expressed as

$$\delta_j = \mathbb{E}[D_i \mid j] = \int d_j(r)\, dF_j(r).$$

Then, the difference in average default rates between the two lender types can be decomposed into two components as follows.

$$\delta_{NB} - \delta_B = \underbrace{\left(\int d_{NB}(r)\, dF_{NB}(r) - \int d_B(r)\, dF_{NB}(r)\right)}_{\text{Conditional-performance Effect}} + \underbrace{\left(\int d_B(r)\, dF_{NB}(r) - \int d_B(r)\, dF_B(r)\right)}_{\text{Composition Effect}} \tag{A1}$$

The conditional-performance effect captures differences in default probabilities conditional on the same observed risk, holding the risk distribution fixed at the NBFI distribution. The composition effect captures the portion of the default-rate gap attributable to differences in the risk-index distributions of loans originated by NBFIs and banks.

The decomposition indicates that borrower composition accounts for most of the NBFI-bank default gap. Differences in the underwriting risk-index distribution explain 86.8 percent of the gap, while the conditional-performance component accounts for the remaining 13.2 percent. This residual is small, suggesting that NBFI loans do not perform substantially worse than bank loans once observed risk is held fixed. This finding is consistent with Fuster et al. (2019), who show that differences in screening on unobservables between banks and NBFIs are limited, as differences in default rates become small after controlling for observable borrower characteristics. In other words, the higher default rate of NBFI loans is driven primarily by the fact that NBFIs' portfolios consists of a larger share of riskier loans.

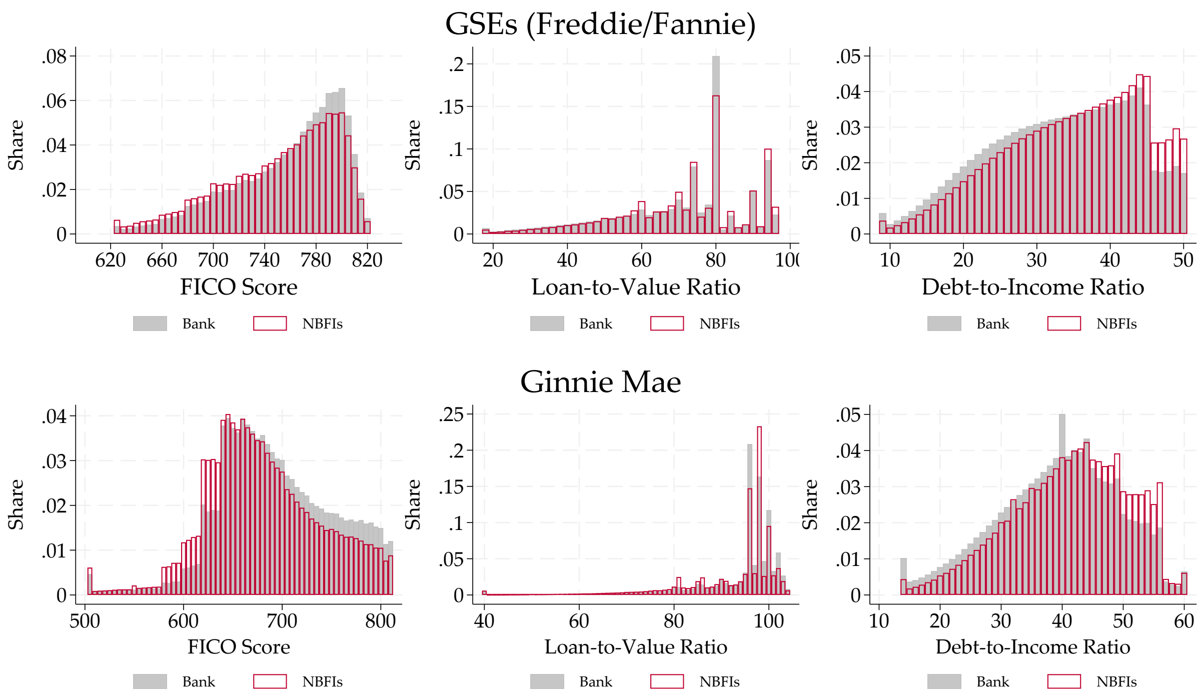
## A.2. Univariate Analysis

While the main text constructs measures summarizing borrower creditworthiness, or the inverse of riskiness, using principal component analysis with HMDA, GSE, and Ginnie Mae data, this section compares bank and NBFI loans across each metric, as in Buchak et al. (2018); Fuster et al. (2019); Jiang et al. (2024).

Figure A1 compares the marginal distributions of FICO, LTV, and DTI by originator type. The upper three panels report loans sold to Fannie Mae and Freddie Mac, while the lower three panels report loans sold to Ginnie Mae.

In the Fannie Mae and Freddie Mac segment, NBFI loans are riskier along the main underwriting margins. NBFI originations place more mass on lower credit scores, especially below 740. They also place more mass at very high LTV values, particularly around 100 percent and above. The DTI distribution shows a similar pattern, with NBFI loans more concentrated in the upper tail, especially above 40 percent and 45 percent. The lower three panels of Figure A1 show that the same risk pattern is stronger in the Ginnie Mae segment. Relative to banks, NBFIs originate more loans with low credit scores particularly below 650. They also originate more loans with high leverage, as reflected in LTV ratios around 90 percent and above, and more loans with high DTI ratios, especially above 40 percent. These distributional differences indicate that NBFI risk is not confined to one underwriting variable. It appears jointly across credit scores, leverage, and debt burden.

**Figure A1.** Distribution of the Characteristics of the Borrowers




**Notes.** The upper panels of the figure plot the marginal distributions of FICO, LTV, and DTI for loans sold to Fannie Mae and Freddie Mac. The lower panels plot the marginal distributions for loans sold to Ginnie Mae. The red line corresponds to NBFI originations and the gray line corresponds to bank originations. The sample includes loans originated from 2010Q1 to 2024Q4. *Sources.* Single-Family Loan-Level Datasets provided by Freddie Mac, Fannie Mae, Ginnie Mae and author's calculations.

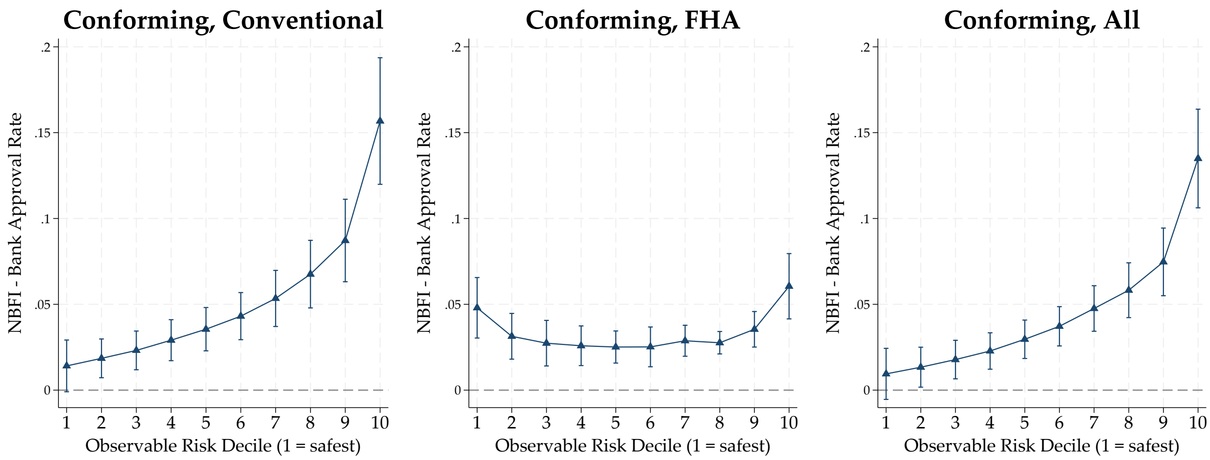
# Appendix B. Robustness Checks on the Approval Difference and Distribution of Applications

## B.1. Approval Difference

To examine more formally whether this difference becomes larger as observable applicant risk increases, I construct an observable risk index using the first principal component of loan size, Debt-to-Income ratio, and income using HMDA data from 2018 to 2024. I normalize the index so that higher values indicate riskier ex ante profiles, corresponding to higher DTI, lower income, and smaller loan amounts. I then divide the index into deciles and interact the NBFI indicator with an indicator for each risk decile.

$$\mathbb{I}\left(Approved_{l,t}\right) = \sum_{d=1}^{10} \beta_d \times \mathbb{I}\left(NBFI_l\right) \times \mathbb{I}\left(Risk_l = d\right) + \sum_{d=1}^{10} \delta_d \times \mathbb{I}\left(Risk_l = d\right) + \Gamma' X_{l,t} + \alpha_{c,t} + \varepsilon_{l,t}. \quad \text{(A2)}$$

**Figure A2.** Estimated NBFI–Bank Approval Rate Differences by Observable Risk Decile




**Notes.** The figure reports estimates of $\beta_d$ from Regression (A2), which measure the approval-rate difference between NBFIs and banks within each decile of the observable risk index. Higher deciles correspond to riskier observable applicant profiles. The left panel reports estimates for conventional conforming loans, and the right panel reports estimates for the full conforming sample. Vertical bars indicate 95% confidence intervals. Standard errors are two-way clustered at the county and lender levels. *Sources.* HMDA and author's calculations.

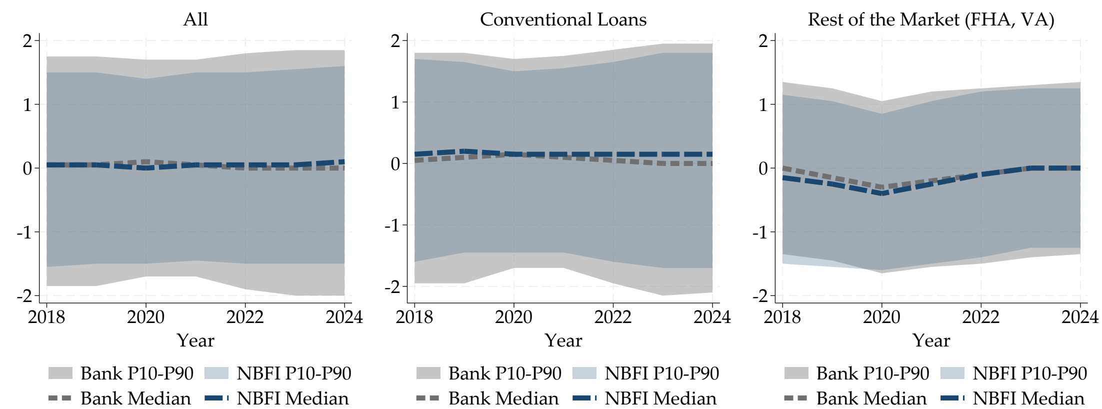
Figure A2 shows the estimated coefficients $\{\beta_d\}_{d=1}^{10}$ for each segment. The approval-rate gap is close to zero among the safest applicants and increases steadily with observable risk, with the largest differences appearing in the highest-risk deciles. This pattern is present for conventional conforming loans and for the full conforming sample, while FHA loans exhibit a relatively constant gap across risk deciles, remaining around 3 to 4 percentage points and rising above 5 percentage points in the highest-risk decile. The results are robust to alternative risk indices, including specifications that incorporate the LTV ratio. These results imply that even for loans that can be sold to third parties, NBFIs are more likely than banks to approve applications with riskier observable profiles, and that the NBFI approval advantage is not uniform across applicants. This pattern is also consistent with the composition of originated loans displayed in Figure 2, as the NBFI share increases among riskier loans while the bank share decreases.

## B.2. Distribution of Applications

In this section, I compare applicant characteristics at the application stage using the first principal component of income, DTI, and loan size, normalized so that a higher value corresponds to more creditworthy borrowers. The measure can be constructed only from 2018 onward because HMDA began reporting borrower information beyond income in 2018.

Figure A3 compares the distribution of applicant risk across lender types. In the full market, the median applicant risk proxy and the 10th-to-90th percentile range are closely aligned between banks and NBFIs. The same pattern holds when the market is divided into conventional loans, which constitute the largest mortgage segment, and government-backed loans, such as FHA and VA loans, whose borrowers generally have riskier credit profiles. Across these segments, applicants to NBFIs do not appear observably riskier than applicants to banks at the application stage.

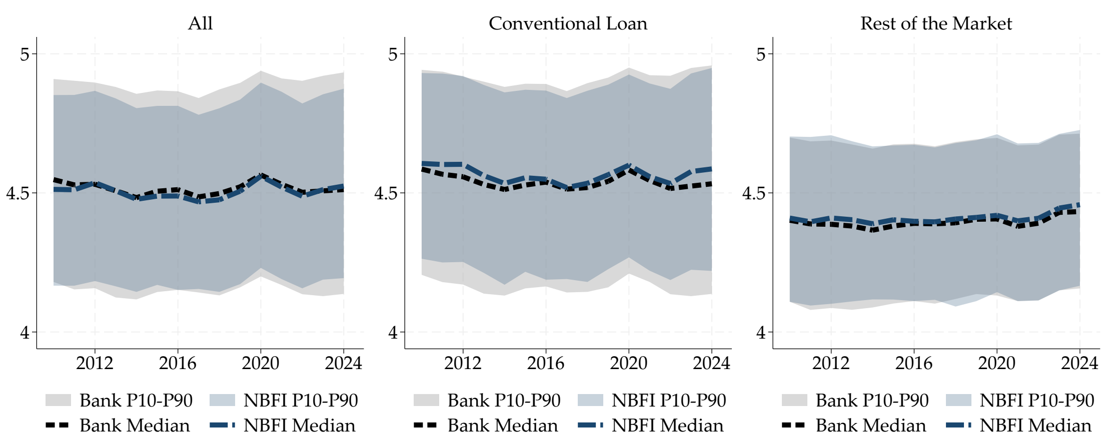
**FIGURE A3.** Risk Proxy Distribution for Applicants




**Notes.** The proxy is constructed as the first principal component of standardized income, loan amount, and DTI from 2018 onward. *Sources.* HMDA and author's calculations.

I further examine applicant sorting using real income, which is available over the full post-crisis sample beginning in 2010. Figure A4 repeats the application-stage comparison using applicants' log real income. The figure shows that the income distribution is broadly stable over time and similar across lender types. The medians and 10th–90th percentile bands are closely aligned for bank and NBFI applications throughout the sample.

**FIGURE A4.** Real Income Distribution of Applicants




**Notes.** Lines report medians and means. Shaded areas report the 10th–90th percentile range. *Sources.* HMDA and author's calculations.

The full market and the conventional loan segment deliver patterns similar to the PCA-based analysis for the 2018–2024 period. The right panel also shows that applicants in FHA, VA, and

FSA/RHS loan segments have lower income distributions than applicants in the conventional loan segment, consistent with the role of these programs in serving lower-income borrowers. Within these government-related segments, however, income distributions remain similar across bank and NBFI applicants. This pattern supports the PCA-based evidence that observable applicant risk is closely aligned across lender types at the application stage.

# Appendix C. Robustness Checks on the Effect of Capital Regulation on NBFI Activities

## C.1. Balance in Pre-Regulation Characteristics

In this section, I compare the pre-regulation characteristics of regions with high and low exposure to regulated banks. I classify regions as high exposure if the regulated-bank market share is above the median and report the standardized differences in local characteristics between the high- and low-exposure groups. The figure shows whether regions with greater regulatory exposure systematically differ from less exposed regions in their demographic and economic characteristics before the regulatory change.

**FIGURE A5.** Balance in Pre-Regulation Characteristics

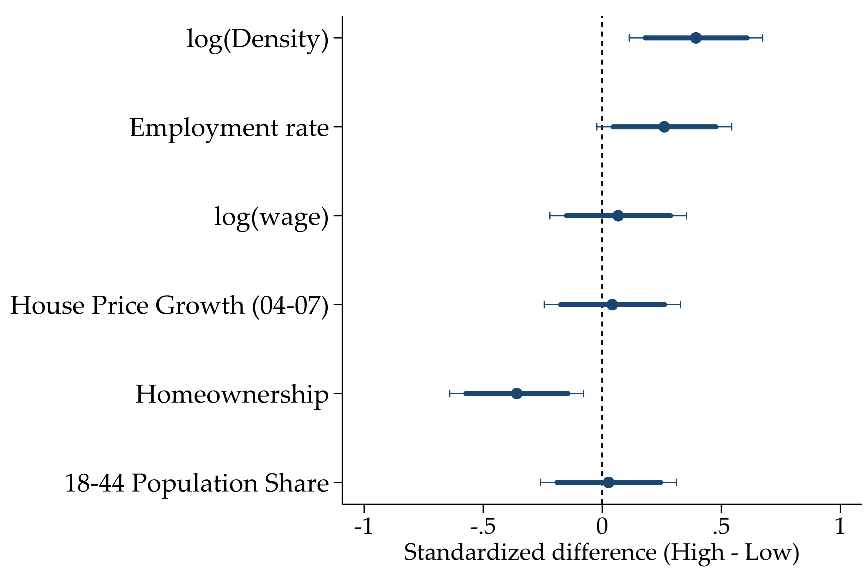



Figure A5 shows the results. Regions with higher regulatory exposure are more densely populated and have higher employment rates, while homeownership rates are lower. In contrast, differences in wages, pre-crisis house price growth, and the share of the population aged 18 to 44 are relatively small and statistically indistinguishable from zero. Overall, the figure indicates that higher-exposure regions differ along some local characteristics, particularly population density, employment, and homeownership, but not systematically across all pre-regulation characteristics.

## C.2. Robustness Checks on Main Findings

In this section, I conduct robustness checks on the main findings from the regional exercise showing that greater exposure to regulation is associated not only with the rise of NBFIs but also with a credit shift toward riskier borrowers and higher subsequent default rates.

I first change the covariates by excluding regulatory measures and by excluding all covariates, as suggested in Altonji et al. (2005) and Oster (2019).

**Figure A6. Dynamic Effects of Bank Regulation on NBFI Share in Origination, Borrowers' Riskiness, and Defaults – Adding Regulatory Controls**

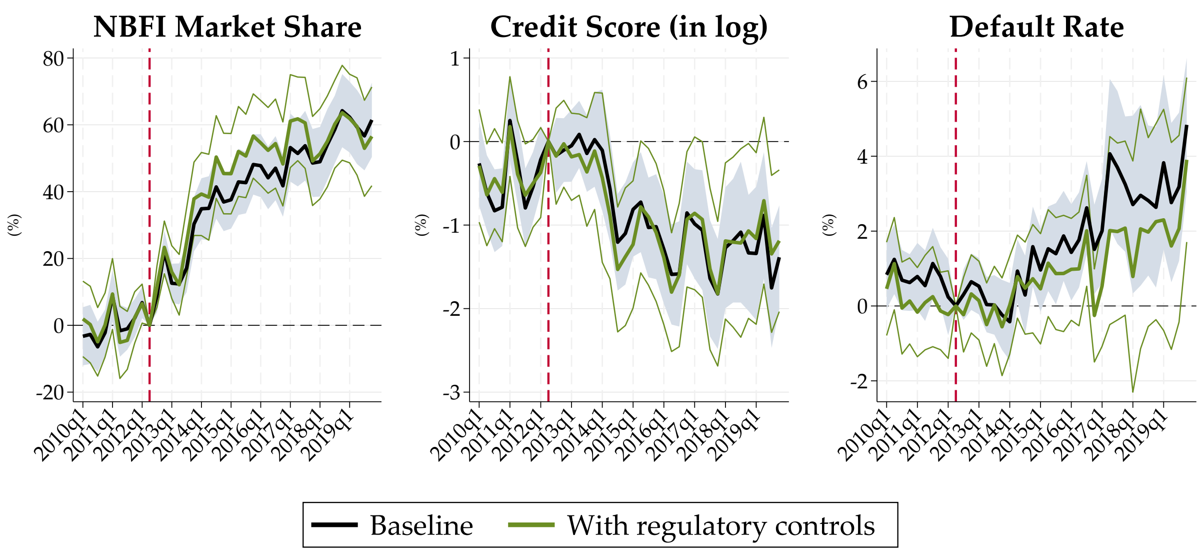
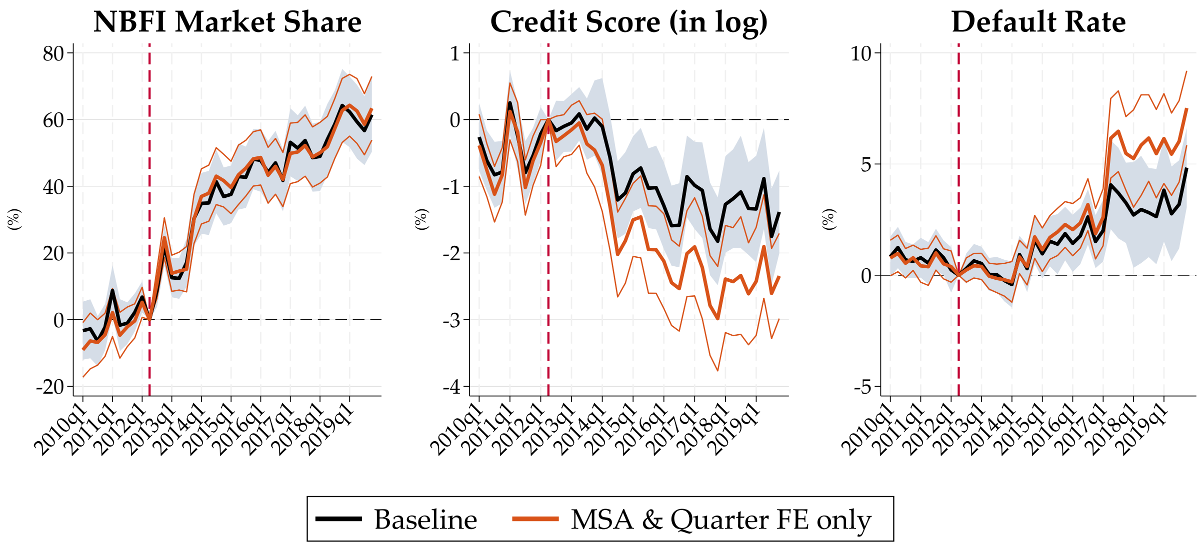



Figure A6 shows the results when regulatory measures are included, and Figure A7 reports the case where only fixed effects are included. The results show that in both cases, the responses become more pronounced while the pre-trends are still maintained. This implies that while the covariates are important for adjusting the magnitude of the effect of regulation on the reshaping of the credit market, the main results are not driven by the choice of covariates.

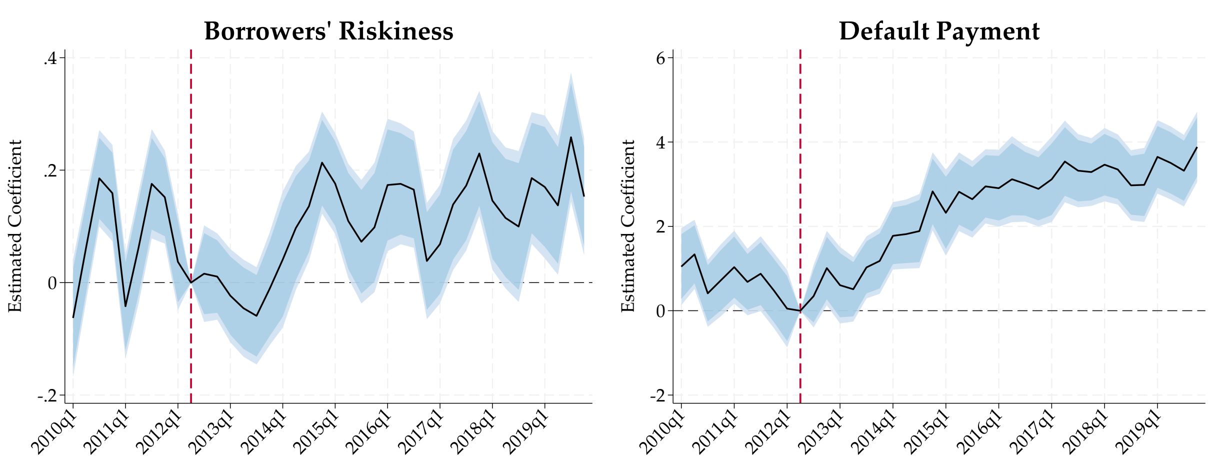
Finally, I estimate the responses of the borrower risk index and defaulted principal. Defaulted principal is calculated as the logarithm of the amount of defaulted principal in each region and quarter. Figure A8 shows the results. The borrower risk index rises after the regulation, while

**Figure A7. Dynamic Effects of Bank Regulation on NBFI Share in Origination, Borrowers' Riskiness, and Defaults – With only TWFE**




defaulted principal also increases in regions with greater exposure to the regulation.

**Figure A8. Dynamic Effects of Bank Regulation on Borrower Risk Index and Defaulted Principal**

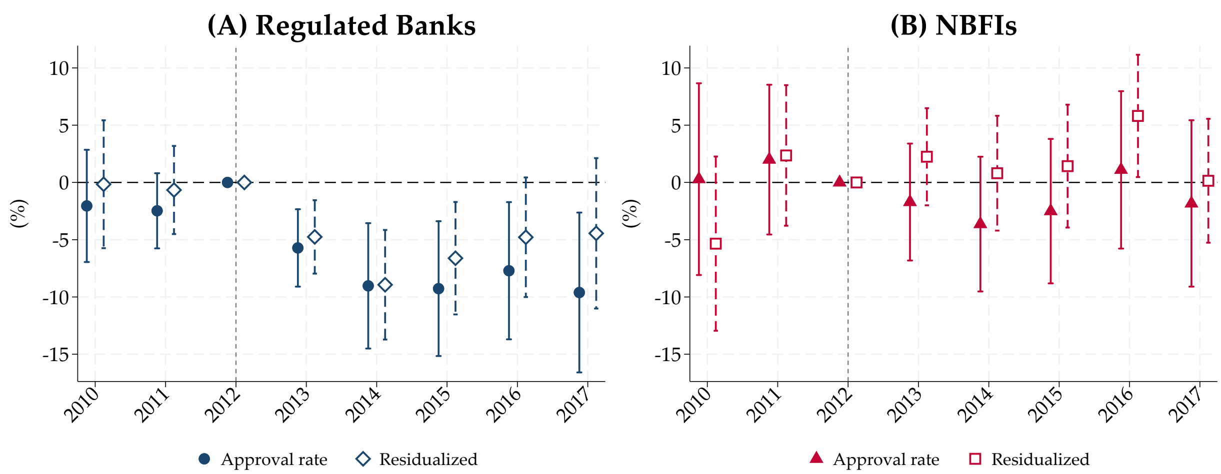


## C.3. Robustness of Approval Rate Responses and NBFI Application Share Responses

In the main text, I show the results of the average approval rate responses after the regulation. The results show that regions with greater exposure to the regulation proxy exhibit lower bank approval rates, while NBFI approval rates remain stable. However, since this measures the raw average approval rate, the composition of applicants could matter.

To address this concern, I first obtain the residual of the approval decision, a dummy variable, by regressing it on observable borrower characteristics, including income, loan size, sex and ethnicity of the borrower, and loan purpose and property type. I then recalculate the average approval measure based on this residualized approval decision for each MSA and each sector.

**FIGURE A9. Dynamic Effects of Bank Regulation on Raw Approval Rates and Residualized Approval Rate**




Note: Confidence interval is 95%.

**Note.** This figure reports the annual event-study estimates $\beta_\tau$ from equation (4), where MSA-level regulatory exposure, $Regulation_m$, is interacted with year indicators. The omitted year is 2012. In Panel (A), the dependent variables are the approval rate and residualized approval rate of banks within each MSA. In Panel (B), the dependent variables are the corresponding approval rates of NBFIs. The specification includes MSA fixed effects, year fixed effects, and pre-Basel III local characteristics interacted with year indicators. Vertical bars denote 95% confidence intervals based on standard errors clustered at the MSA level. *Source.* HMDA

Figure A9 shows the results. The left panel compares the results in the main text with the residualized approval rate. The initial declines from both measures are almost identical, while the persistence decreases after 2016. The right panel shows the approval rate of NBFIs and shows that the residualized approval rate also remains stable after the regulation, while there is a slight increase in 2016 that vanishes in 2017.

Then, I test the response of the NBFI share of applications after the regulation.

**FIGURE A10. Dynamic Effects of Bank Regulation on NBFI Shares of Applications and Originations**

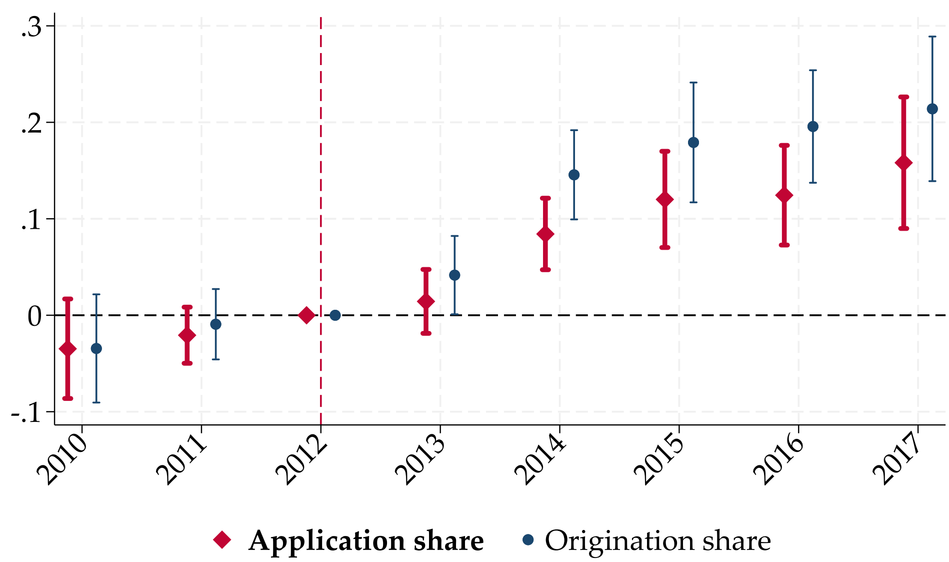



Figure A10 shows the results. The results show that the NBFI share of applications also increases after the regulation is implemented. In terms of magnitude, the increase in the NBFI share of applications is smaller than the increase in the share of originations. The results could partially reflect changes in the approval-rate gap across the two sectors.

## C.4. Alternative Treatment Measure

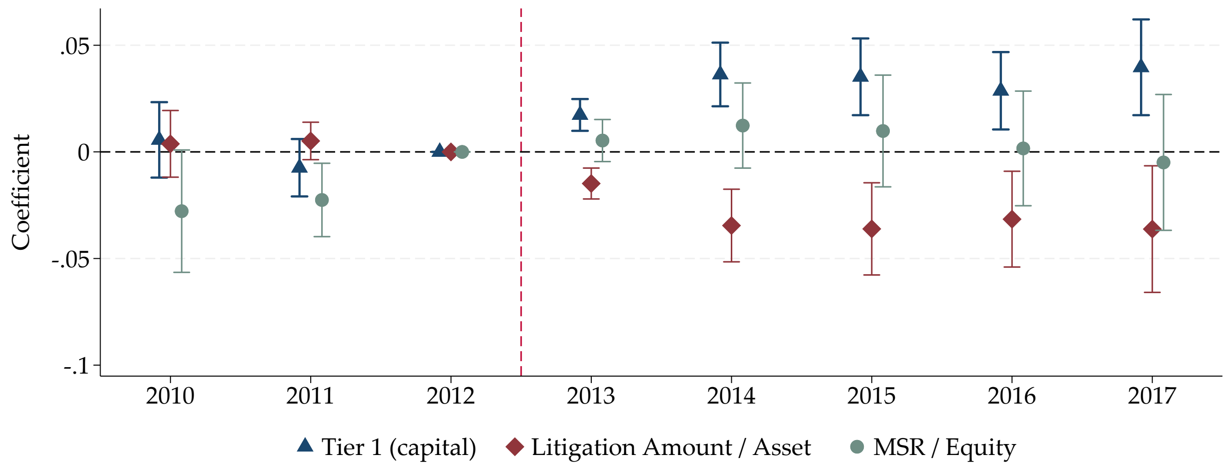
In this section, I construct an alternative measure that captures exposure to regulation. Instead of using the market-share-weighted average of an indicator variable for regulatory exposure, I calculate the regional-level capital ratio as the market-share-weighted average of the capital ratios of regulated banks. I first construct three bank-level measures for initial capitalization, mortgage-related legal exposure, and mortgage servicing rights. The capital measure, $Cap_b$, is bank $b$'s Tier 1 risk-based capital ratio in 2008. The legal-overhang measure, $Legal_b$, is the cumulative value of major mortgage-related settlements and enforcement actions through 2012, scaled by the bank's total assets in 2008. The MSR measure, $MSR_b$, is the bank's mortgage servicing assets relative to equity in 2008. The capital and MSR measures are constructed from FR Y-9C data. I aggregate these bank-level measures to the county level using banks' pre-Basel III mortgage market shares. Each county-level measure is then standardized by its cross-sectional standard deviation. For $Cap_c$, I reverse the sign after standardization so that a higher value indicates greater exposure to banks with weaker initial capitalization. Thus, counties with higher $Cap_c$ were more exposed to banks facing greater capital pressure before the regulatory changes.

Also, to increase the market coverage from GSE loans to the entire mortgage market, I utilize the HMDA dataset. I then augment the baseline local event-study specification by jointly interacting $Cap_c$, $Legal_c$, and $MSR_c$ with year indicators.

$$
\begin{aligned}
Y_{c,t} = & \sum_{\tau=2010,\ \tau\neq 2012}^{2017} \beta_\tau \mathbb{I}[t=\tau] \times Cap_c + \sum_{\tau=2010,\ \tau\neq 2012}^{2017} \theta_\tau \mathbb{I}[t=\tau] \times Legal_c \\
& + \sum_{\tau=2010,\ \tau\neq 2012}^{2017} \phi_\tau \mathbb{I}[t=\tau] \times MSR_c + \mathbf{X}'_{ct}\Gamma + \alpha_c + \delta_t + \varepsilon_{c,t}.
\end{aligned} \tag{A3}
$$

The dependent variable, $Y_{c,t}$, is the NBFI share of mortgage originations by dollar volume in county $c$ and year $t$. The omitted year is 2012. County fixed effects, $\alpha_c$, absorb time-invariant differences across local mortgage markets, while year fixed effects, $\delta_t$, absorb aggregate shocks common to all counties. The vector $\mathbf{X}_{ct}$ includes pre-period housing boom and bust measures, log population, homeownership, and unemployment, each interacted with year indicators. The regression is weighted by total county mortgage origination volume, and standard errors are clustered at the county level.

**FIGURE A11. Dynamic Effects of Capital Requirement and Confounder on NBFI market share**




**Note.** This figure reports the annual event-study estimates from equation (A3). The plotted coefficients correspond to county-level exposure to capital pressure, legal overhang, and mortgage servicing rights, each interacted with year indicators. The omitted year is 2012. The dependent variable is the NBFI share of mortgage originations. All exposure measures are standardized by their cross-sectional standard deviations, and the capital measure is normalized so that higher values indicate weaker initial capitalization. The specification includes county fixed effects, year fixed effects, and pre-period local characteristics interacted with year indicators. Vertical bars denote 95% confidence intervals based on standard errors clustered at the county level. *Sources.* HMDA, FR Y-9C, and public litigation records.

Figure A11 reports the joint event-study estimates. The coefficients on capital pressure become positive after 2013 and remain positive through 2017, indicating that counties initially more exposed to weakly capitalized banks experienced a larger subsequent increase in the NBFI origination share. In contrast, legal-overhang exposure is negatively associated with the NBFI share after 2013, which is inconsistent with litigation-related retrenchment explaining the baseline increase in NBFI lending. MSR exposure exhibits no persistent positive post-2013 effect and is generally estimated imprecisely. Taken together, the results indicate that the expansion of NBFIs is associated with banks' broader capital pressure rather than with mortgage-related legal overhang or the direct capital treatment of MSRs.

## C.5. Within-Bank Analysis

To address the concern that regulated banks may have reduced lending in response to supervisory pressures other than the new capital requirements, I conduct a bank-level analysis that exploits cross-sectional variation in banks' pre-announcement balance-sheet characteristics. In particular, I take Tier 1 leverage capitalization as a proxy for exposure to the Basel III reform and additionally take into account mortgage servicing rights (MSR) holdings, legal exposure, and vulnerability to the supervisory stress tests.

I control for stress-test vulnerability because banks with lower initial capital ratios may also have been expected to experience larger projected losses under the adverse scenario. The estimated effect of the initial capital ratio could then capture responses to stress testing rather than adjustment to the Basel III capital requirements. I therefore measure stress-test exposure using each bank's projected stress loss relative to its pre-announcement total assets.[36]

The estimating equation is

$$\begin{aligned} y_{it} = {} & \beta_1 \left(\text{Low Capital}_i \times \text{Post}_t\right) + \beta_2 \left(\text{MSR Exposure}_i \times \text{Post}_t\right) \\ & + \beta_3 \left(\text{Legal Exposure}_i \times \text{Post}_t\right) + \beta_4 \left(\text{Stress Exposure}_i \times \text{Post}_t\right) \\ & + \Gamma \left(X_i \times \text{Post}_t\right) + \alpha_i + \lambda_t + \varepsilon_{it}, \end{aligned} \tag{A4}$$

where $y_{it}$ is bank $i$'s mortgage origination activity in year $t$. Bank fixed effects, $\alpha_i$, absorb time-invariant differences across banks, while year fixed effects, $\lambda_t$, absorb aggregate changes in the economy. Low Capital is defined as the negative standardized value of the bank's pre-announcement Tier 1 leverage ratio, so that a higher value indicates weaker initial capitalization and greater potential adjustment pressure. MSR Exposure is the ratio of mortgage servicing rights to equity, and Legal Exposure is legal exposure scaled by total assets. Stress Exposure is projected stress losses divided by pre-announcement total assets. The vector $X_i$ includes pre-announcement profitability and mortgage-asset exposure, both measured relative to total assets. All exposure measures are fixed before the Basel III announcement and interacted with $\text{Post}_t$, which equals one beginning in 2013.

Table A1 shows the results. Consistent with the results in Appendix C.4, capital requirements are an important factor that can explain the decline in originations after the implementation of the regulation. Importantly, mortgage servicing rights are also an important margin that can explain the reduction, through which tighter capital requirements also operate. While I do not explicitly model the secondary market with servicing rights, regulation of mortgage servicing rights through capital requirements still operates as an important margin.

[36] Stress losses equal the sum of projected loan, securities, trading and counterparty, and other losses reported in the 2012 CCAR, scaled by total assets. More specifically, stress losses comprise projected losses on first-lien mortgages, junior liens and HELOCs, C&I loans, CRE loans, credit cards, other consumer and other loans, realized losses on AFS/HTM securities, trading and counterparty losses, and fair-value and goodwill-impairment losses, scaled by total assets.

**Table A1.** Within-Bank Analysis of Mortgage Originations

| | Log Mortgage Originations | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Low Capital × Post | $-0.080^{***}$ | $-0.101^{***}$ | $-0.066^{**}$ |
| | (0.025) | (0.030) | (0.022) |
| MSR Exposure × Post | $-0.111^{***}$ | $-0.116^{**}$ | $-0.078^{***}$ |
| | (0.030) | (0.040) | (0.025) |
| Legal Exposure × Post | 0.619 | $0.902^{*}$ | $0.800^{**}$ |
| | (0.442) | (0.495) | (0.352) |
| Stress Exposure × Post | | $0.084^{*}$ | $0.183^{**}$ |
| | | (0.046) | (0.066) |
| Profitability × Post | | | $0.256^{**}$ |
| | | | (0.112) |
| Mortgage-Asset Exposure × Post | | | 0.222 |
| | | | (0.360) |
| Bank fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 107 | 107 | 107 |
| $R^2$ | 0.969 | 0.972 | 0.974 |
| Within $R^2$ | 0.197 | 0.270 | 0.318 |

*Notes.* The dependent variable is the log of bank-level mortgage originations. Low Capital is the negative standardized value of the bank's pre-announcement Tier 1 leverage ratio. MSR Exposure is mortgage servicing rights relative to equity. Legal Exposure is legal exposure relative to total assets. Stress Exposure is projected stress losses in the 2012 CCAR relative to pre-announcement total assets. Profitability and Mortgage-Asset Exposure are measured relative to total assets. All exposure measures are fixed at their pre-announcement values and interacted with Post, which equals one beginning in 2013. All specifications include bank and year fixed effects. Standard errors clustered at the bank level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

# Appendix D. Proof of Proposition

## D.1. Proof of Proposition 1

The first-order condition with respect to the loan rate is

$$R^L = \frac{\varepsilon}{\varepsilon - 1} \frac{1}{1 - d(q)} \left( R^f + s(q) \right). \tag{A5}$$

and it follows that the per-dollar margin at the equilibrium can be rewritten as

$$(1 - d(q))R^L - R^f - s(q) = \frac{R^f + s(q)}{\varepsilon - 1}. \tag{A6}$$

The first-order condition with respect to underwriting stringency is

$$-d'(q)R^L - s'(q) + \left((1 - d(q))R^L - R^f - s(q)\right)\left(\frac{p'(q)}{p(q)} + \frac{A'(q)}{A(q)}\right) = 0. \tag{A7}$$

where

$$\frac{A'(q)}{A(q)} = \frac{\partial \log L^{app}(R^L, q)}{\partial q}$$

under the assumption of constant elasticity of substitution with respect to loan rates. Substituting (A5) and (A6) into (A7) gives the reduced underwriting condition

$$\Phi(q, R^f) \equiv -\frac{\varepsilon}{\varepsilon - 1}\left(R^f + s(q)\right)\frac{d'(q)}{1 - d(q)} - s'(q) + \frac{R^f + s(q)}{\varepsilon - 1}\left(\frac{p'(q)}{p(q)} + \frac{A'(q)}{A(q)}\right) = 0. \tag{A8}$$

Let $\widehat{\Pi}(q, R^f)$ denote profit *after* optimizing over the loan rate. By the envelope theorem,

$$\frac{\partial \widehat{\Pi}(q, R^f)}{\partial q} = p(q)L^{app}\left(R^{L*}(q, R^f), q\right)\Phi(q, R^f).$$

At an interior optimum, $\Phi(q^*, R^f) = 0$ holds. Therefore,

$$\frac{\partial^2 \widehat{\Pi}(q^*, R^f)}{\partial q^2} = p(q^*)L^{app}\left(R^{L*}(q^*, R^f), q^*\right)\Phi_q(q^*, R^f).$$

Since originated lending is positive, the second-order condition implies

$$\Phi_q(q^*, R^f) < 0. \tag{A9}$$

Differentiating (A8) with respect to $R^f$, holding $q$ fixed, gives

$$\Phi_{R^f}(q, R^f) = -\frac{\varepsilon}{\varepsilon - 1}\frac{d'(q)}{1 - d(q)} + \frac{1}{\varepsilon - 1}\left(\frac{p'(q)}{p(q)} + \frac{A'(q)}{A(q)}\right). \tag{A10}$$

Equations (A8) and (A10) imply

$$\Phi(q, R^f) = \left(R^f + s(q)\right)\Phi_{R^f}(q, R^f) - s'(q).$$

Evaluating this expression at the optimum gives

$$\big(R^f + s(q^*)\big)\Phi_{R^f}(q^*, R^f) = s'(q^*).$$

Since $R^f + s(q^*) > 0$ and $s'(q^*) > 0$,

$$\Phi_{R^f}(q^*, R^f) > 0. \tag{A11}$$

Applying the implicit function theorem to (A8) yields

$$\frac{dq^*(R^f)}{dR^f} = -\frac{\Phi_{R^f}(q^*(R^f), R^f)}{\Phi_q(q^*(R^f), R^f)}.$$

Combining (A9) and (A11), we obtain

$$\frac{dq^*(R^f)}{dR^f} > 0.$$

Thus, a higher funding cost raises the intermediary's optimal underwriting stringency.

## D.2. Proof of Proposition 2

This section decomposes and quantifies the underlying channels through which total defaults respond to tighter bank capital requirements. Let $\omega_{NB}$ denote the NBFI share of applications, as defined in equation (19). Then, originations in each sector $j$ satisfy

$$L_j = \underbrace{p_j(q_j)}_{\text{Approval Rate}} \times \underbrace{\omega_j}_{\text{Application Share}} \times \underbrace{L^{app}}_{\text{Total Applications}}.$$

and aggregate originated lending is therefore

$$L = L_B + L_{NB} = [p_{NB}(q_{NB})\omega_{NB} + p_B(q_B)(1-\omega_{NB})]\, L^{app}.$$

Define $\pi_{NB}$ as the NBFI share of aggregate *originations*. Its relation to the application share $\omega_{NB}$ is expressed in odds form as

$$\frac{\pi_{NB}}{1-\pi_{NB}} = \frac{\omega_{NB}}{1-\omega_{NB}}\frac{p_{NB}(q_{NB})}{p_B(q_B)}. \tag{A12}$$

### D.2.1. Default Measures

Given the definitions of $\pi_{NB}$ and $\pi_B = 1 - \pi_{NB}$, the origination-weighted aggregate default rate is

$$d^{\text{agg}} = \pi_{NB} d_{NB}(q_{NB}) + (1 - \pi_{NB}) d_B(q_B), \tag{A13}$$

and total defaulted principal can then be written as

$$\begin{aligned} \mathcal{D} &= d_{NB}(q_{NB}) L_{NB} + d_B(q_B) L_B \\ &= L \times [\pi_{NB} d_{NB}(q_{NB}) + (1 - \pi_{NB}) d_B(q_B)] \\ &= L \times d^{\text{agg}}. \end{aligned} \tag{A14}$$

### D.2.2. Decomposition

Differentiating total defaulted principal with respect to $\nu$ gives

$$\frac{\mathrm{d}\mathcal{D}}{\mathrm{d}\nu} = L \frac{\mathrm{d}d^{\text{agg}}}{\mathrm{d}\nu} + d^{\text{agg}} \frac{\mathrm{d}L}{\mathrm{d}\nu}. \tag{A15}$$

The first component captures changes in the default rate for a given amount of aggregate originated credit, while the second captures changes in total defaults arising from the response of aggregate lending.

The response of the aggregate default rate can be decomposed by taking the total derivative with respect to capital regulation tightness $\nu$ as

$$\frac{\mathrm{d}d^{\text{agg}}}{\mathrm{d}\nu} = \underbrace{[d_{NB}(q_{NB}) - d_B(q_B)] \frac{\mathrm{d}\pi_{NB}}{\mathrm{d}\nu}}_{\textbf{1. Origination reallocation}} + \underbrace{\pi_{NB} d'_{NB}(q_{NB}) \frac{\mathrm{d}q_{NB}}{\mathrm{d}\nu}}_{\textbf{2. Within-NBFI underwriting}} + \underbrace{(1 - \pi_{NB}) d'_B(q_B) \frac{\mathrm{d}q_B}{\mathrm{d}\nu}}_{\textbf{3. Within-bank underwriting}}. \tag{A16}$$

Equation (A16) shows a decomposition of the aggregate default rate response into one between-sector margin and two within-sector margins. The first term holds sector-specific default rates fixed and captures changes in the composition of originations across banks and NBFIs, which account for both application migration and differences in underwriting standards. Because NBFI loans have a higher default rate than bank loans in equilibrium, a difference that arises due to the looser lending standards they apply, an increase in $\pi_{NB}$ raises the aggregate default rate. The second term captures changes in the default rate conditional on NBFI origination. The third term captures the corresponding change in default risk conditional on bank origination.

To further decompose the first term, the origination-reallocation channel, I derive the semi-elasticity of the NBFI origination odds as

$$\frac{\mathrm{d}}{\mathrm{d}v}\log\left(\frac{\pi_{NB}}{1-\pi_{NB}}\right)=\frac{1}{\pi_{NB}(1-\pi_{NB})}\frac{\mathrm{d}\pi_{NB}}{\mathrm{d}v},$$

which implies

$$\frac{\mathrm{d}\pi_{NB}}{\mathrm{d}v}=\pi_{NB}(1-\pi_{NB})\frac{\mathrm{d}}{\mathrm{d}v}\log\left(\frac{\pi_{NB}}{1-\pi_{NB}}\right) \tag{A17}$$

Combining equation (A12) and the application-allocation equation (19) gives

$$\frac{\pi_{NB}}{1-\pi_{NB}}=\frac{\omega_{NB}}{1-\omega_{NB}}\frac{p_{NB}(q_{NB})}{p_B(q_B)}=\frac{\psi_{NB}}{1-\psi_{NB}}\left(\frac{p_{NB}(q_{NB})}{p_B(q_B)}\right)^{\eta}\left(\frac{R^{\ell}_{NB}}{R^{\ell}_{B}}\right)^{-\varphi}\times\frac{p_{NB}(q_{NB})}{p_B(q_B)}. \tag{A18}$$

Hence, the total derivative of the NBFI share in origination to capital requirement tightness $v$, which is $\mathrm{d}\pi_{NB}/\mathrm{d}v$ can be rewritten as

$$\begin{aligned}\frac{\mathrm{d}\pi_{NB}}{\mathrm{d}v}&=\pi_{NB}(1-\pi_{NB})\times\frac{\mathrm{d}}{\mathrm{d}v}\log\left(\frac{\pi_{NB}}{1-\pi_{NB}}\right)\\&=\pi_{NB}(1-\pi_{NB})\times\\&\quad\Bigg[\underbrace{\varphi\left(\frac{\mathrm{d}\log R^{\ell}_{B}}{\mathrm{d}v}-\frac{\mathrm{d}\log R^{\ell}_{NB}}{\mathrm{d}v}\right)}_{\substack{\textbf{1.1 Relative Loan Rate}\\\textbf{Application Reallocation}}}+\underbrace{\eta\left(\frac{\mathrm{d}\log p_{NB}(q_{NB})}{\mathrm{d}v}-\frac{\mathrm{d}\log p_B(q_B)}{\mathrm{d}v}\right)}_{\substack{\textbf{1.2 Approval-probability}\\\textbf{Application Reallocation}}}+\underbrace{\left(\frac{\mathrm{d}\log p_{NB}(q_{NB})}{\mathrm{d}v}-\frac{\mathrm{d}\log p_B(q_B)}{\mathrm{d}v}\right)}_{\textbf{1.3 Approval screening}}\Bigg].\end{aligned} \tag{A19}$$

The first two terms capture changes at the application stage. The relative loan rate component captures the reallocation of applications induced by changes in relative loan rates, while the approval-probability component captures the reallocation of applications induced by changes in relative approval probabilities. As tighter capital requirements increase the bank loan rate $R^{\ell}_{B}$ and lower $p_B(q_B)$, more applications are submitted to NBFIs. The final term arises when applications are processed and converted into actual originations. Holding application shares fixed, a change in relative approval probabilities changes the relative amount of credit originated by banks and NBFIs. Once the response of aggregate originated loans, $L$, to $v$ is taken into account, the condition under which a tighter capital requirement increases total defaults can be derived.

# Appendix E. Borrower Application, Default, and Aggregation

## E.1. Applications and timing

The representative borrower household consists of a unit measure of members indexed by $i \in [0,1]$ who face idiosyncratic application, approval, and repayment risk and share resources for consumption. Member $i$ submits an application $L^{app}_{i,t}$, and total applications satisfy

$$L^{app}_t = \int_0^1 L^{app}_{i,t}\, di. \tag{A20}$$

Each application's observable creditworthiness is measured by $x_{i,t}$, where higher values indicate safer applicants. At time $t$, the household chooses $C^b_t$, $N^b_t$, and $L^{app}_t$. Each member submits one application to one lender and cannot reapply after rejection within the same period. Applicants observe posted loan rates and lender-level approval probabilities before applying, but they do not observe lenders' underwriting stringency or their individual approval realizations. Members supply labor at date $t$, and household consumption is allocated after approved loans are originated, using current labor income and new loan proceeds net of payments on loans originated at $t-1$. At date $t+1$, idiosyncratic repayment shocks determine default on loans originated at $t$.

## E.2. Application Allocation Decision

In this subsection, I explain how each member $i$ decides where to apply. Time subscripts are omitted throughout this subsection for simplicity. There are two lending sectors $j \in \{B, NB\}$, which represent banks and NBFIs, respectively, with each sector consisting of a unit measure of differentiated lenders $k \in \mathcal{K}_j$. Lender $k$ in sector $j$ posts a loan rate $R^{\ell}_{k,j}$ and chooses an underwriting standard $q_{k,j}$, which determines its approval probability $p_j(q_{k,j})$.

Applicant $i$ chooses the lender offering the highest effective application value,

$$(J_i, K_i) \in \arg \max_{j\in\{B,NB\},\, k\in\mathcal{K}_j} \left\{ \frac{e_{i,k,j}\, \left(\bar{p}_j\right)^{\eta/\varphi} \left(\frac{p_j(q_{k,j})}{\bar{p}_j}\right)^{\eta/\epsilon^{\ell}_j}}{R^{\ell}_{k,j}} \right\}. \tag{A21}$$

This captures the idea that member $i$ seeks an offer with a lower effective loan rate and a higher chance of obtaining the loan.

First, $e_{i,k,j}$ captures application preference shocks across offers, which are reduced-form matching heterogeneity terms used to generate application allocation across lenders. The parameter $\epsilon_j^\ell$ captures substitution across lenders within sector $j$ with respect to loan rates, while $\varphi$ governs substitution across lending sectors.

The parameter $\eta$ governs the response of applications to approval probabilities. I impose the same approval elasticity on within-sector and across-sector competitiveness. To do so, let $\bar{p}_j$ denote the sector-level approval environment perceived by applicants. An individual financial intermediary takes $\bar{p}_j$ as given when choosing its own loan rate and underwriting standard. The borrower then chooses based not only on the sector-level approval rate but also, in principle, on within-sector approval differences. In a sector-symmetric equilibrium, $\bar{p}_j = p_j(q_j)$, and the borrower ultimately responds to sector-level differences.

I assume that the vector of application preference shocks is drawn from the nested Fréchet distribution following Herreño (2023).

$$\Pr\left(e_{i,k,j} \leq z_{kj} \text{ for all } k, j\right) = \exp\left\{-\sum_{j\in\{B,NB\}} \psi_j \left(\int_{\mathcal{K}_j} \mathcal{T}_{kj} z_{kj}^{-\epsilon_j^\ell}\, dk\right)^{\frac{\varphi}{\epsilon_j^\ell}}\right\}, \tag{A22}$$

where $\psi_j > 0$, with $\psi_B + \psi_{NB} = 1$, captures sector-level non-price attractiveness. The term $\mathcal{T}_{kj} > 0$ captures each lender's specific non-price attractiveness, such as accessibility or prior relationships, and is normalized according to

$$\int_{\mathcal{K}_j} \mathcal{T}_{kj}\, dk = 1.$$

The nesting parameters satisfy $0 < \varphi \leq \epsilon_j^\ell$ and $\varphi > 1$.

### E.2.1. Application allocation

For a given sector $j$, substituting the deterministic component of (A21) into (A22) gives sector competitiveness

$$s_j = \psi_j \left(\bar{p}_j\right)^\eta \left[\int_{\mathcal{K}_j} \mathcal{T}_{kj} \left(\frac{p_j(q_{k,j})}{\bar{p}_j}\right)^\eta \left(R_{k,j}^\ell\right)^{-\epsilon_j^\ell}\, dk\right]^{\frac{\varphi}{\epsilon_j^\ell}}, \tag{A23}$$

Applications are allocated across sectors according to

$$\omega_j = \frac{s_j}{\sum_{m\in\{B,NB\}} s_m}. \tag{A24}$$

Conditional on applying to sector $j$, the share of applications received by lender $k$ is

$$\nu_{k|j} = \frac{\mathcal{T}_{kj}\left(\frac{p_j(q_{k,j})}{\bar{p}_j}\right)^{\eta}\left(R^{\ell}_{k,j}\right)^{-\epsilon^{\ell}_j}}{\int_{\mathcal{K}_j}\mathcal{T}_{k'j}\left(\frac{p_j(q_{k',j})}{\bar{p}_j}\right)^{\eta}\left(R^{\ell}_{k',j}\right)^{-\epsilon^{\ell}_j}\,dk'}. \tag{A25}$$

Application size is assumed to be common across household members. Choice probabilities therefore also determine the shares of aggregate application face value,

$$L^{app}_{k,j} = \nu_{k|j} \times \omega_j \times L^{app}. \tag{A26}$$

Because each lender is atomistic, it takes $\bar{p}_j$, $\omega_j$, and the sector aggregates as given when choosing its own loan rate and underwriting standard. Equation (A25) therefore implies

$$\frac{\partial \log L^{app}_{k,j}}{\partial \log R^{\ell}_{k,j}} = -\epsilon^{\ell}_j \qquad \text{and} \qquad \frac{\partial \log L^{app}_{k,j}}{\partial \log p_j(q_{k,j})} = \eta. \tag{A27}$$

Lender-level originations are

$$L^{orig}_{k,j} = p_j(q_{k,j})L^{app}_{k,j}. \tag{A28}$$

It follows that

$$\frac{\partial \log L^{orig}_{k,j}}{\partial q_{k,j}} = (1+\eta)\frac{p'_j(q_{k,j})}{p_j(q_{k,j})}. \tag{A29}$$

Thus, the individual lender internalizes both the direct effect of underwriting on the fraction of applications approved and the induced response of its application inflow. This is the origin of the $1+\eta$ term in the underwriting first-order conditions.

### E.2.2. Allocation in the Symmetric Equilibrium

I consider a symmetric equilibrium in which

$$q_{k,j} = q_j, \qquad R^{\ell}_{k,j} = R^{\ell}_j \tag{A30}$$

for each sector $j$. In the symmetric equilibrium, the sectoral application share is given by

$$\omega_j = \frac{\psi_j\left[p_j(q_j)\right]^{\eta}\left(R^{\ell}_j\right)^{-\varphi}}{\sum_{m\in\{B,NB\}}\psi_m\left[p_m(q_m)\right]^{\eta}\left(R^{\ell}_m\right)^{-\varphi}}, \qquad L^{app}_j = \omega_j L^{app}. \tag{A31}$$

### E.2.3. Composition of applicant pools

As I discuss in the main text, the baseline does not assume sorting, in that application preferences are independent of members' creditworthiness.

$$\left\{e_{i,k,j}\right\}_{k\in\mathcal{K}_j,\, j\in\{B,NB\}} \perp x_i, \qquad x_i \sim F_x. \tag{A32}$$

This condition implies that the underlying creditworthiness distribution of applications processed by each lender $k$ in sector $j$ is invariant, while the volume changes proportionally at each level of creditworthiness.

$$\Pr\left(x_i \leq x \mid (J_i, K_i) = (j,k)\right) = F_x(x). \tag{A33}$$

## E.3. Approval Decision

The underwriting standard of lender $k$ in sector $j$ induces the approval probability

$$p_{k,j}(q_{k,j,t}) = 1 - F_x\left(\tau_{k,j}(q_{k,j,t})\right), \tag{A34}$$

where $\tau'_{k,j}(q) > 0$ and therefore $p'_{k,j}(q) < 0$. $\tau(q)$ can be understood as a cutoff that determines whether applicants' creditworthiness is high enough to be approved for loans, and it is assumed to increase with the tightness of the underwriting standard. Equation (A33) implies that the applicant creditworthiness distribution is invariant, and therefore the approval function $p_{k,j}(\cdot)$ is a fixed function of the underwriting standard.

Applicants observe $p_{k,j}$ before applying, but they do not observe $q_{k,j,t}$, the approval threshold $\tau_j(q_{k,j,t})$, or the decisions on their applications. Lenders internalize applicants' behavior when choosing $q_{k,j,t}$.

Once applications are allocated to lender $k$ in sector $j$, it applies its own underwriting standard and approves an application if $x_{i,t} \geq \tau_j(q_{k,j,t})$. In the symmetric equilibrium, each sector's origination can then be computed as

$$L^{orig}_{j,t} = \omega_{j,t} p_j(q_{j,t}) L^{app}_t. \tag{A35}$$

## E.4. Repayment and borrower-family aggregation

Given the no-sorting assumption on borrowers, the distribution of creditworthiness among approved loans is determined by the underwriting stringency that the lender applies. For loans originated at date $t$, repayment shocks determine individual default at $t+1$, and the sector-level default rate is summarized by $d_{j,t} = d_j(q_{j,t})$. The detailed derivation is provided in Appendix F.

The repayment at date $t+1$ from sector-$j$ loans originated at date $t$ is then

$$\left(1 - d_j(q_{j,t})\right) R^{\ell}_{j,t} L^{orig}_{j,t}. \tag{A36}$$

Under the definition of the aggregate loan rate below

$$R^{\ell}_t = \left( \frac{\sum_{j\in\{B,NB\}} \psi_j \left[p_j(q_{j,t})\right]^{\eta} \left(R^{\ell}_{j,t}\right)^{-\varphi}}{\sum_{j\in\{B,NB\}} \psi_j \left[p_j(q_{j,t})\right]^{\eta}} \right)^{-1/\varphi}, \tag{A37}$$

the aggregate repayment wedge $d_t$ is defined as

$$\sum_{j\in\{B,NB\}} \left(1 - d_{j,t}\right) R^{\ell}_{j,t} L^{orig}_{j,t} = \left(1 - d_t\right) R^{\ell}_t L^{orig}_t. \tag{A38}$$

The object $d_t$ is the wedge that makes $(R^{\ell}_t, L^{orig}_t)$ sufficient for aggregate repayment. This accounting wedge is distinct from the origination-weighted default rate used to measure aggregate credit risk.

At date $t$, the household pools current labor income and proceeds from newly originated loans, net of payments on loans originated at $t-1$, and shares these resources across all members. Labor income is $W_t N^b_t$, while repayment shocks enter the budget through loan payments. Given the definition of the aggregate loan rate and default wedge, aggregating the member-level settlement outcomes therefore gives

$$P_t C^b_t + \left(1 - d_{t-1}\right) R^{\ell}_{t-1} L^{orig}_{t-1} = W_t N^b_t + L^{orig}_t. \tag{A39}$$

where loans are in nominal terms. Let $c^b_{i,t}$ and $n^b_{i,t}$ denote member-level consumption and labor, and define

$$C^b_t = \int_0^1 c^b_{i,t}\, di, \qquad N^b_t = \int_0^1 n^b_{i,t}\, di. \tag{A40}$$

Household welfare before imposing the symmetric risk-sharing allocation is

$$\mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^b)^t \int_0^1 \mathcal{U}(c_{i,t}^b, n_{i,t}^b)\, di. \tag{A41}$$

Because members have identical preferences, face the same wage, and share resources for consumption regardless of individual approval or default status, the symmetric allocation satisfies $c_{i,t}^b = C_t^b$ and $n_{i,t}^b = N_t^b$ for almost every $i$.[37]

$$\int_0^1 \mathcal{U}(c_{i,t}^b, n_{i,t}^b)\, di = \mathcal{U}(C_t^b, N_t^b). \tag{A42}$$

The same aggregation applied to the application-stage loan-to-income restriction gives $L_t^{app} \leq \theta W_t N_t^b$. The representative borrower household therefore solves

$$\max_{\{C_t^b, N_t^b, L_t^{app}\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^b)^t \mathcal{U}(C_t^b, N_t^b) \tag{A43}$$

subject to equation (A39), $L_t^{orig} = \bar{p}_t L_t^{app}$, and $L_t^{app} \leq \theta W_t N_t^b$, where $\bar{p}_t$ is the average approval rate.

# Appendix F. Derivation of Approval and Default Schedules

## F.1. Approval Function

Assume that applicant creditworthiness $x$ follows a logistic distribution with location $\mu_x$ and scale $s_x > 0$,

$$F_x(x) = \frac{1}{1 + \exp\left(-\frac{x-\mu_x}{s_x}\right)}. \tag{A44}$$

The distribution $F_x$ is the distribution of creditworthiness used in the baseline application block. Suppose that underwriting stringency $q$ shifts the latent approval threshold according to

$$\tau_j(q) = \bar{\tau}_j + \gamma_j q, \qquad \gamma_j > 0. \tag{A45}$$

[37] As in Forlati and Lambertini (2011), household consumption insurance coexists with individual loan default. Their default mechanism relies on housing collateral, whereas I use a reduced-form repayment-capacity rule.

An application is approved when $x \geq \tau_j(q)$. The approval probability is therefore

$$\begin{aligned} p_j(q) &= 1 - F_x\left(\tau_j(q)\right) \\ &= \frac{1}{1 + \exp\left(\frac{\bar{\tau}_j - \mu_x}{s_x}\right)\exp\left(\frac{\gamma_j}{s_x}q\right)} = \frac{1}{1 + b_{0,j}\exp\left(b_{1,j}q\right)}. \end{aligned} \tag{A46}$$

The reduced-form parameters satisfy

$$b_{0,j} = \exp\left(\frac{\bar{\tau}_j - \mu_x}{s_x}\right), \qquad b_{1,j} = \frac{\gamma_j}{s_x} > 0. \tag{A47}$$

Hence, the logistic creditworthiness distribution and the affine approval threshold deliver exactly the approval function used in the main text,

$$p_j(q) = \frac{1}{1 + b_{0,j}\exp\left(b_{1,j}q\right)}, \qquad p_j'(q) = -b_{1,j}p_j(q)\left[1 - p_j(q)\right] < 0. \tag{A48}$$

**Default Condition and Portfolio Default** Consider a borrower approved by sector $j$. Repayment capacity in the following period is

$$Y_{i,t+1} = \overline{Y}_j \exp\left(\rho_j x_{i,t}\right)\varepsilon_{i,t+1}, \qquad \rho_j > 0, \tag{A49}$$

where $x_{i,t}$ denotes borrower creditworthiness and $\varepsilon_{i,t+1}$ is an idiosyncratic repayment shock. Repayment capacity is specific to the loan, is not an additional household resource, and cannot be altered by household consumption, labor supply, or transfers. A borrower defaults when realized repayment capacity falls below a fixed threshold $\underline{Y}_j^D$. In the baseline, the shock distribution is fixed within each sector and independent of creditworthiness and application preferences, with independent draws across borrowers. I assume that this threshold is independent of the contractual loan rate, consistent with the evidence in Foote et al. (2008) and Bosshardt et al. (2025).

Under the lower-tail assumption for the repayment shock, the borrower-level default probability can be written as

$$g_j(x) = \overline{d}_j \exp\left(-\lambda_j x\right), \qquad \lambda_j > 0. \tag{A50}$$

The repayment parameters, the distress threshold, and the shock distribution are summarized by $\overline{d}_j$ and $\lambda_j$.[38] Since $\lambda_j > 0$, borrowers with higher creditworthiness have lower default risk.

[38] Over the relevant range, assume $\Pr(\varepsilon_{i,t+1} \leq z) = \pi_j z^{\xi_j}$. Combining this condition with the repayment equation and the default threshold gives $\overline{d}_j = \pi_j(\underline{Y}_j^D/\overline{Y}_j)^{\xi_j}$ and $\lambda_j = \xi_j\rho_j$. Thus the primitive parameters enter borrower default through these two objects.

Underwriting affects the default rate by changing the composition of approved loans. In the baseline model, application preference shocks are independent of borrower creditworthiness, so changes in application volume do not change the underlying distribution of $x$ faced by each sector. Underwriting stringency instead determines which borrowers in that distribution receive credit. If sector $j$ approves borrowers with $x \geq \tau_j(q)$, the default rate among originated loans is

$$d_j^{\text{exact}}(q) = \mathbb{E}\left[g_j(x) \mid x \geq \tau_j(q)\right]. \tag{A51}$$

With independent shocks across a continuum of borrowers, this conditional expectation gives the sector-level default rate. Since application size is common across members, this is also the principal-weighted rate, and the economy-wide rate is the origination-weighted average across sectors.

A higher underwriting standard raises the approval threshold and removes borrowers with lower creditworthiness from the originated pool. Since borrower-level default risk decreases with creditworthiness, the portfolio default rate also decreases with underwriting stringency.

The exact portfolio default rate determines how borrower selection translates underwriting into default risk, but its curvature depends on the full distribution of approved borrowers. Around the steady-state underwriting standard $q_j$, the exact portfolio default rate satisfies

$$\begin{aligned}\log d_j^{\text{exact}}(q) &\approx \log d_j^{\text{exact}}(q_j) + \frac{d_j^{\text{exact}\prime}(q_j)}{d_j^{\text{exact}}(q_j)}(q - q_j) \\ &= \log d_j^{\text{exact}}(q_j) - \delta_{1,j}(q - q_j),\end{aligned} \tag{A52}$$

where $\delta_{1,j} = -d_j^{\text{exact}\prime}(q_j)/d_j^{\text{exact}}(q_j) > 0$. Hence, $d_j^{\text{exact}}(q) \approx d_j^{\text{exact}}(q_j)\exp[-\delta_{1,j}(q - q_j)]$, which gives the exponential schedule around the steady state.

The calibration disciplines the sectoral default level and the local default gradient rather than this curvature. I therefore parameterize the default schedule with a constant semi-elasticity, which gives

$$d_j(q) = \delta_{0,j}\exp\left(-\delta_{1,j}q\right), \qquad \delta_{1,j} > 0. \tag{A53}$$

Here, $\delta_{0,j}$ determines the default level and $\delta_{1,j}$ determines the response of default to underwriting around the steady state.

# Appendix G. Calibration Details

## G.1. Externally Set Parameters

This section provides a summary of externally set parameters

**Table A2.** Externally Set Parameters and Targets

| Parameter | Description | Value | Target or Source |
|---|---|---|---|
| *Panel A. Saver preferences and portfolios* | | | |
| $\beta_s$ | Saver discount factor | 0.995 | Annual policy rate 2% |
| $1/\sigma_s,\ 1/\sigma_b$ | Intertemporal elasticities of substitution | 1 | Standard |
| $\phi$ | Labor-supply curvature | 2/3 | Herreño and Pedemonte (2025) |
| $\alpha$ | Deposit weight in liquidity | 0.734 | $D/F = 3.58$ |
| $\vartheta$ | Deposit–MMF substitution | 3.17 | d'Avernas and Vandeweyer (2024) |
| $\Xi_L$ | Liquidity-service weight | 0.023 | Saver money-fund level FOC |
| *Panel B. Borrower preferences and credit demand* | | | |
| $\beta_b$ | Borrower discount factor | 0.985 | Gatt (2025) |
| $\chi$ | Borrower population share | 0.39 | Iacoviello (2005) |
| $\theta$ | Loan-to-income limit | 1.90 | Campbell and Cocco (2015), HMDA |
| $\psi_B$ | Bank loan-preference weight | 0.43 | Bank application share, HMDA |
| $\varphi$ | Bank–NBFI loan substitution | 8 | Buchak et al. (2024), See Text |
| $\eta$ | Approval-access elasticities | 1 | Agarwal et al. (2024), See Text |
| *Panel C. Financial intermediary sector* | | | |
| $\gamma_B$ | Bank equity-payout parameter | 0.126 | Reference target $E_B/L_B = 0.164$ |
| $\gamma_{NB}$ | NBFI equity-payout parameter | 0.014 | Reference target $E_{NB}/L_{NB} = 0.249$ |
| $\xi$ | Capital-requirement cost scale | 0.0012 | Ulate (2021) |
| $\nu$ | Bank regulatory requirement | 0.06 | Regulatory capital requirement |
| $\epsilon^{\ell}_B,\ \epsilon^{\ell}_{NB}$ | Within-sector loan substitution | 360 | Ulate (2021); Abadi et al. (2023) |
| $\zeta$ | Default-resolution resource cost | 0.10 | An and Cordell (2021) |
| *Panel D. New Keynesian block* | | | |
| $\theta_{prod}$ | Intermediate goods substitution | 3.9 | Abadi et al. (2023) |
| $\kappa_\pi$ | Phillips-curve slope | 0.0062 | Hazell et al. (2022) |
| $\rho_R$ | Taylor-rule smoothing | 0.72 | Hofmann et al. (2024) |
| $\phi_\pi$ | Taylor-rule inflation response | 2.11 | Hofmann et al. (2024) |
| $\phi_y$ | Taylor-rule output response | 0.26 | Hofmann et al. (2024) |

## G.2. Calibration of Underwriting, Approval, Default, and Screening Costs

This appendix describes how the underwriting index and the approval and default schedules are disciplined quantitatively. The calibration uses a common observable applicant-quality scale for the approval and default blocks. The approval block measures the location and slope of the underwriting standard from application decisions. The default block measures how subsequent default risk varies with borrower quality and maps that gradient into the local portfolio-default schedule. Screening costs and effective default-loss retention are then recovered from the lender optimality conditions.

### G.2.1. Applicant Quality Index

Let $r_i$ denote the observable applicant-risk index used in the application analysis in Section 2.3.2, where higher values indicate riskier observable applicant profiles. The index is constructed as the first principal component of applicant income, debt-to-income ratio, and loan amount. The underlying variables are standardized in the pooled sample of bank and NBFI applications, including approved and denied applications, and a single set of principal-component loadings is estimated in that pooled sample and applied to every observation.

For the structural calibration, it is convenient to express the same underlying index as applicant quality rather than applicant risk. I therefore define

$$x_i = -r_i, \tag{A54}$$

so that higher $x_i$ denotes a safer observable applicant profile. No lender-specific, market-specific, year-specific, or approval-specific restandardization is performed. The approval and default calibration blocks therefore use the same underlying principal-component score and differ from the empirical application-risk index only by the sign normalization in (A54).

This applicant-quality index should not be confused with the separate originated-loan risk index used in the loan-performance decomposition in Section 2.1, which is constructed from credit score, debt-to-income ratio, and loan-to-value ratio.

### G.2.2. Classification-Based underwriting standard

Let $g$ index a lender, county, and year cell. Let $A_{ig}$ equal one when application $i$ is approved and zero otherwise. For any candidate policy location $c$, define the classification score

$$Q_g(c) = \sum_{i \in g} \left[ A_{ig} \mathbf{1}\{x_i \geq c\} + (1 - A_{ig}) \mathbf{1}\{x_i < c\} \right]. \tag{A55}$$

The empirical underwriting-policy location in cell $g$ is

$$\widehat{q}_g \in \arg\max_c Q_g(c). \tag{A56}$$

When several adjacent values attain the maximum, I use the midpoint of the maximizing interval. Cells in which the maximum corresponds to approving every applicant or denying every applicant are treated as boundary solutions and are retained only in the diagnostic calculations described below.

The object $\widehat{q}_g$ is a classification-based summary of the location of the observed approval policy. It is not interpreted as a literal legal cutoff, and approval decisions do not need to follow a deterministic one-dimensional rule.

To connect $\widehat{q}_g$ to the structural underwriting variable, let $q_g^*$ denote the latent structural policy location. I impose the following maintained measurement restriction. In a neighborhood of the calibrated steady state, there exists a sector-specific mapping $h_j$ such that

$$\widehat{q}_g = a_j + h_j(q_g^*) + u_g, \qquad h_j'(q_g^*) > 0, \tag{A57}$$

where $u_g$ is cell-level measurement error. The mapping is assumed to be locally stable across lender-county-year cells within a sector. The monotonicity restriction means that a cell classified as having a higher policy location is also interpreted as having tighter structural underwriting locally.

Because the level and units of the latent policy variable are otherwise arbitrary, I normalize

$$a_j = 0, \qquad h_j'(q_j^*) = 1 \tag{A58}$$

at the sectoral steady state. The model underwriting variable $q$ is therefore measured locally in the same units as the classification-based policy index. This is a maintained measurement assumption rather than a consequence of the one-dimensional classifier.

To match the definition used in the main text, the sectoral steady-state underwriting standard is the simple mean of the cell-level policy locations

$$q_j = \frac{1}{G_j} \sum_{g\,:\,j(g)=j} \widehat{q}_g, \qquad j \in \{B, NB\}, \tag{A59}$$

where $G_j$ is the number of admissible lender-county-year cells in sector $j$. The same equal-weighted definition is used in the quantitative implementation.

The estimated $\widehat{q}_g$ is a simple summary of the location of approval decisions in each lender, county, and year cell. It should not be read as a literal rule that determines every approval decision. I use it as the empirical measure of the underwriting standard, with a higher value indicating tighter underwriting. The model variable $q$ is normalized to use the same local scale.

### G.2.3. Approval Schedule

The model approval schedule is

$$p_j(q) = \frac{1}{1 + b_{0,j} \exp\left(b_{1,j} q\right)}, \qquad b_{1,j} > 0. \tag{A60}$$

I estimate the slope $b_{1,j}$ from the relationship between approval rates and underwriting standards across lender-county-year cells. The regression is estimated separately for banks and NBFIs

$$\log\left(\frac{P_g}{1-P_g}\right) = \alpha_j - b_{1,j}\widehat{q}_g + \lambda_{\ell(g),c(g)} + \tau_{c(g),t(g)} + \varepsilon_g. \tag{A61}$$

Here, $P_g$ is the approval rate in cell $g$. The regression includes lender-by-county and county-by-year fixed effects and is weighted by the number of applications in the cell. In the actual estimation, the approval rate and the underwriting measure are constructed from different random halves of the applications in each cell.[39]

Let $P_j$ denote the application-weighted approval rate in sector $j$. Once $b_{1,j}$ is estimated, $b_{0,j}$ is chosen so that the model matches the observed sectoral approval rate at $q_j$

$$p_j(q_j) = P_j. \tag{A62}$$

This gives

$$b_{0,j} = \left(\frac{1}{P_j} - 1\right)\exp\left(-b_{1,j}q_j\right). \tag{A63}$$

#### G.2.4. Default Schedule

The model needs a measure of how default risk changes when underwriting becomes tighter. I obtain this slope from loan-level performance. The applicant-quality index is observed for originated loans, so the data directly show how subsequent default risk varies with borrower quality. A tighter underwriting standard shifts originations toward safer applicants. I therefore use the loan-level relationship between borrower quality and default as the empirical slope of the default schedule. In the benchmark, one unit of tighter underwriting is assumed to shift average originated borrower quality by one unit on the same standardized scale.

I estimate the loan-level default gradient using originated loans matched between HMDA and the GSE loan-performance data. The outcome is serious delinquency within eight quarters of origination. For each sector, I estimate

$$\mathbb{E}\left[\mathbf{1}\left\{\text{serious delinquency within eight quarters}\right\} \mid x_i, Z_i, j\right] = \exp\left(\alpha_j - \beta_j x_i + Z_i'\Gamma_j\right). \tag{A64}$$

[39]The split sample avoids using the same applications to construct both the approval rate and the underwriting measure. It also addresses sampling error in the cell-level cutoff. I pair the cutoff from one half with the approval rate from the other half, use the cross-half cutoff covariance to correct attenuation, repeat the split twenty times, and use the median valid estimate.

The baseline specification is estimated by Poisson quasi-maximum likelihood. The controls in $Z_i$ are the same controls used in the loan-performance analysis. The coefficient $\beta_j$ is estimated separately for banks and NBFIs. A positive $\beta_j$ means that safer borrowers have lower subsequent default risk.

The model default schedule is

$$d_j(q) = \delta_{0,j} \exp\left(-\delta_{1,j} q\right). \tag{A65}$$

Under the benchmark unit pass-through described above, the estimated loan-level gradient gives the slope of the model default schedule.[40]

$$\delta_{1,j} = \beta_j. \tag{A66}$$

Appendix H varies this pass-through assumption and recalibrates the default schedule under the alternative values.

The level of the default schedule is set to match the observed sectoral default rate. The empirical outcome is measured over eight quarters, while the model is quarterly, so I divide the observed eight-quarter serious-delinquency rate by eight to obtain the quarterly target. The corresponding annualized default rates are 1.76 percent for banks and 4.51 percent for NBFIs.

Let $D_{j,q}$ denote the quarterly default target. I choose $\delta_{0,j}$ so that

$$d_j(q_j) = D_{j,q}. \tag{A67}$$

Therefore,

$$\delta_{0,j} = D_{j,q} \exp\left(\delta_{1,j} q_j\right). \tag{A68}$$

The default response used in the underwriting condition is

$$d'_j(q_j) = -\delta_{1,j} D_{j,q}. \tag{A69}$$

[40]To see the mapping, write originated borrower quality locally as $X_{ij}(q) = \mu_j + \vartheta_j q + U_{ij}$. Combining this with the estimated loan-level relation $\Pr(\text{serious delinquency} \mid X_{ij}, j) \propto \exp(-\beta_j X_{ij})$ gives $d_j(q) \propto \exp(-\vartheta_j \beta_j q)$. Hence $\delta_{1,j} = \vartheta_j \beta_j$. The benchmark sets $\vartheta_j = 1$, so $\delta_{1,j} = \beta_j$. Because $\beta_j$ is estimated separately for banks and NBFIs, the mapping is sector specific.

## G.3. Estimating the Bank–NBFI Substitution Elasticity

I estimate the substitution elasticity $\varphi$ using the allocation of mortgage applications between banks and NBFIs in HMDA. I first construct county–year observations for each sector.

The estimating equation follows from the ratio of sectoral application shares in equation (19), while setting the approval elasticity to $\eta = 1$. I estimate

$$\log\left(\frac{L^{app}_{B,c,t}}{L^{app}_{NB,c,t}}\right) - \log\left(\frac{p_{B,c,t}}{p_{NB,c,t}}\right) = \alpha_c + \tau_t - \varphi \log\left(\frac{R^{\ell}_{B,c,t}}{R^{\ell}_{NB,c,t}}\right) + u_{c,t}, \tag{A70}$$

where $\alpha_c$ and $\tau_t$ denote county and year fixed effects. I interpret the negative of the coefficient on the relative loan rate as a conditional calibration estimate of $\varphi$ under the restriction $\eta = 1$. It is not intended to provide a causal estimate of the loan demand.

HMDA reports interest rates for originated loans. I adjust these rates for borrower and loan characteristics using a hedonic regression that controls for income, loan amount, LTV, DTI, loan maturity, and loan purpose. I then calculate average adjusted interest rates within each sector, county, and year. The estimated results show that $\varphi = 9.33$, with a standard error of 2.114, clustered at the county level.

I additionally examine sensitivity by repeating the same fixed-effects OLS regression for alternative fixed values of $\eta$ between zero and two. The resulting estimates range from 5.28 to 8.20, showing that the estimated values remain within the range suggested by Paul et al. (2024).

## G.4. Additional Evidence on Default Loss Internalization

I examine whether differences in loan pricing and subsequent loan performance support the calibrated ordering of default loss internalization between banks and NBFIs, $\kappa_B$ and $\kappa_{NB}$. Using GSE loan-level data, I compare how interest rates and subsequent defaults vary with observable borrower risk across the two sectors.

I use the riskiness proxy that I constructed in Section 2.2, which is an observable borrower-risk index from credit scores, loan-to-value ratios, and debt-to-income ratios. The index loads negatively on credit scores and positively on LTV and DTI ratios, so that a higher value corresponds to a riskier observable borrower profile relative to the local origination cohort.

The estimated regression model is

$$Y_{i,t} = \beta_1 \,\text{Risk}_i + \beta_2 \,\mathbb{I}[NBFI_i] \times \text{Risk}_i + \alpha_{m_i,t} + \lambda_{s_i,t} + \phi_{c_i} + \varepsilon_{i,t},$$

where $Y_{i,t}$ is either the interest rate or an indicator for default for loan $i$ originated in quarter $t$.

Default is defined as a loan becoming 60 or more days past due within two years of origination, as in the main empirical analysis. The variable $\text{Risk}_i$ is the borrower-risk index, and $\mathbb{I}[NBFI_i]$ equals one for loans originated by NBFIs. The coefficient $\beta_1$ measures the response to borrower risk for banks, while $\beta_2$ measures the difference in this response between NBFIs and banks. The corresponding NBFI slope is $\beta_1 + \beta_2$.

MSA-by-quarter fixed effects, $\alpha_{m_i,t}$, absorb local demand conditions and market-level shocks common to loans originated in the same MSA and quarter. Sector-by-quarter fixed effects, $\lambda_{s_i,t}$, absorb sector-specific differences in average pricing and default levels across origination quarters. In the pricing regressions, these controls account for sector-level shifts in funding conditions and interest-rate levels. They also absorb the NBFI main effect, so that the comparison concerns risk sensitivity rather than the average difference between sectors. FICO-by-LTV cell fixed effects, $\phi_{c_i}$, are included as a proxy for G-fee following the loan-level price adjustment (LLPA) grid. This helps distinguish differences in risk pricing between banks and NBFIs from differences associated with where their loans fall in that grid. I include the same cell fixed effects in the default regression to compare pricing and loan performance conditional on the same underwriting categories. Standard errors are clustered at the MSA level.

**Table A3.** Borrower Risk, Loan Pricing, and Subsequent Default

| | Interest Rate | | Default |
|---|---|---|---|
| | (1) Basis points | (2) Basis points | (3) Percentage points |
| Borrower Risk | 12.739*** | 6.162*** | 0.616*** |
| | (0.155) | (0.148) | (0.022) |
| NBFI × Borrower Risk | −0.641*** | −0.916*** | 0.035** |
| | (0.145) | (0.152) | (0.017) |
| MSA-by-quarter fixed effects | ✓ | ✓ | ✓ |
| Sector-by-quarter fixed effects | ✓ | ✓ | ✓ |
| FICO-by-LTV (g-fee) fixed effects | – | ✓ | ✓ |
| Observations | 34,371,223 | 34,371,223 | 34,371,223 |
| MSA clusters | 468 | 468 | 468 |
| $R^2$ | 0.840 | 0.845 | 0.046 |

*Notes.* The dependent variable is the mortgage interest rate in columns (1) and (2) and an indicator for default within two years of origination in column (3). Interest-rate coefficients and standard errors are reported in basis points, and default coefficients and standard errors in percentage points. Higher values of Borrower Risk indicate riskier observable borrower profiles. Standard errors clustered at the MSA level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Sources.* GSE loan-level data and author's calculations.

Table A3 shows the results. Columns (1) and (2) indicate that interest rates increase less steeply with borrower risk for NBFIs than for banks. The interaction coefficient is negative and statistically significant at the 1 percent level in both specifications, and its magnitude increases after including

FICO-by-LTV cell fixed effects. In column (2), a one-unit increase in the risk index is associated with an interest-rate increase of 6.16 basis points for banks and 5.25 basis points for NBFIs. The NBFI pricing slope is therefore 14.87 percent smaller.

Column (3) shows the opposite pattern for default. A one-unit increase in the risk index is associated with an increase in the default probability of 0.616 percentage points for banks and 0.651 percentage points for NBFIs. The NBFI default slope is 5.60 percent larger, and the interaction coefficient is statistically significant at the 5 percent level. Thus, the weaker pricing response of NBFIs is accompanied by a stronger increase in subsequent defaults, rather than a smaller increase in default risk.

# Appendix H. Sensitivity Analysis and Extension

## H.1. Sensitivity Analysis

**Key Parameters** In this section, I conduct sensitivity analysis by changing key parameter values. First, I vary the elasticity of substitution with respect to the loan rate, $\varphi$, taking values of 6, 8, 11, and 15. This exercise is motivated by the estimates of substitution across financing sources discussed in Paul et al. (2024) and Buchak et al. (2024). A higher elasticity allows more borrowers to shift toward NBFIs when bank capital requirements increase, leading to larger increases in the aggregate default rate and total defaulted payments. At the lowest value considered, $\varphi = 6$, both measures still increase, although the increase in total defaulted payments is smaller.

Second, I vary $\eta$, which determines how strongly approval probabilities affect borrowers' choice between bank and NBFI credit and, through loan originations, lenders' incentives to screen applicants. The results remain similar across the alternative values of $\eta$. Approval probabilities change only modestly as capital requirements increase, and $\eta$ changes symmetrically across the two sectors. Therefore, the relative approval component that determines the allocation of applications changes little. In addition, each specification is recalibrated to match the same benchmark targets, and the responses are measured relative to its own baseline. Thus, the main results are not sensitive to the strength of the approval-rate channel.

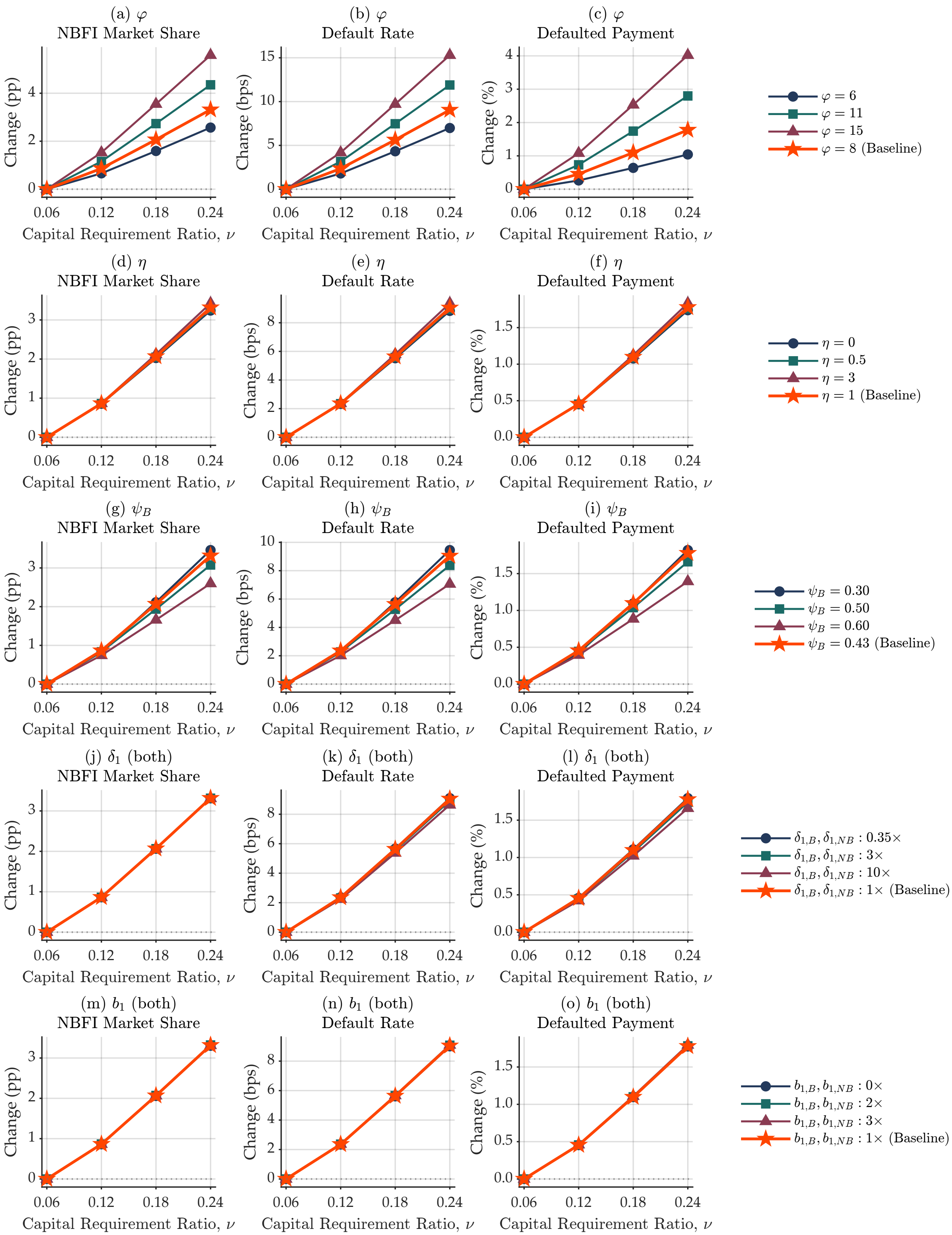
Third, I vary $\psi_B$, which summarizes the preference toward the banking sector. The effect of capital requirements on aggregate credit risk depends on the initial market shares. As the share of banks increases, the effect of regulation on aggregate credit risk becomes smaller. This is because the amount of applications that migrate to NBFIs depends on the initial shares of NBFIs and banks. Over the parameter values considered here, a larger initial bank share is associated with a smaller increase in the NBFI share as capital requirements tighten, so the increase in aggregate credit risk is also smaller.

**Approval and Default Schedule** One concern is that the reduced-form parameters of the default and approval schedules may themselves depend on the policy environment. In particular, NBFIs facing large equity losses may change which borrowers they approve, so holding these parameters fixed could miss an adjustment in their lending behavior. To examine this concern, I first re-estimate both schedules separately for each origination year from 2018 to 2024. I cannot reject equality of the approval slopes across years when accounting for correlation within lenders. The default slopes exhibit some variation, but the slope of neither schedule differs significantly across years. I complement this empirical exercise with a sensitivity analysis that varies the default and approval slopes in both sectors over a wider range.

First, I jointly vary $\delta_{1,B}$ and $\delta_{1,NB}$, which determine how default probabilities respond to underwriting in each sector. I multiply both parameters by the same factor, considering 0.35, 1, 3, and 10 times their benchmark values. For each parameter pair, I recalibrate $\delta_{0,j}$ so that the benchmark default probability remains unchanged at the calibrated underwriting level. Therefore, this exercise changes the semi-elasticity of default risk to underwriting. The results are similar because policy-induced changes in underwriting remain close to the calibration point, particularly for NBFIs. As a result, even different default-schedule slopes operate on relatively small changes in underwriting, while the effects of capital requirements on sectoral migration and aggregate credit risk remain qualitatively the same.

Second, I jointly vary $b_{1,B}$ and $b_{1,NB}$, which determine how approval probabilities respond to underwriting stringency. I consider 0, 1, 2, and 3 times their benchmark values and recalibrate the remaining approval-function parameters to preserve the benchmark approval probabilities. Unlike $\eta$, which governs how borrowers respond to approval probabilities when choosing a lender, $b_{1,j}$ governs how those probabilities change when lenders adjust underwriting. When both slopes are zero, approval probabilities do not respond to underwriting, but borrowers can still shift between banks and NBFIs in response to loan rates. The results remain similar across these specifications. As the capital requirement rises from 6% to 24%, the aggregate default rate increases by 9.01–9.10 basis points, and total defaulted payments rise by 1.78–1.79%. Thus, the increase in aggregate credit risk does not depend on a strong response of approval probabilities to underwriting.

**FIGURE A12.** Sensitivity Analysis



## H.2. Extensions

### H.2.1. Two-Type Borrowers

I relax the baseline no-sorting assumption by introducing a latent safe type $S$ and a risky type $R$. Borrowers observe their own type, but lenders only know the population share of each type and apply the same approval schedule to both types.[41]

The two borrower types differ in their responses to loan rates and approval probabilities. Given the loan rate and approval probability offered by each lender, a type $T \in \{S, R\}$ borrower allocates applications according to

$$\omega_{T,j} = \frac{\psi_j p_j(q_j)^{\eta_T}(R_j^{\ell})^{-\varphi_T}}{\sum_{k\in\{B,NB\}} \psi_k p_k(q_k)^{\eta_T}(R_k^{\ell})^{-\varphi_T}}, \tag{A71}$$

where $\eta_T$ determines the response to approval probabilities and $\varphi_T$ determines the response to loan rates. Therefore, risky and safe borrowers can sort differently across banks and NBFIs even though lenders cannot observe their types.

Because lenders apply the same approval schedule to both types, the share of type $T$ among lender $j$'s originated loans is

$$\pi_{T,j} = \frac{\mu_T \omega_{T,j}}{\sum_{T'\in\{S,R\}} \mu_{T'}\omega_{T',j}}. \tag{A72}$$

Thus, $\pi_{T,j}$ can differ from the population share $\mu_T$ because the two types can choose lenders differently. The default rate also differs across borrower types. I assume

$$d_{T,j}(q_j) = \delta_{0,T,j}\exp(-\delta_{1,j}q_j), \qquad \delta_{0,R,j} = \lambda_R \delta_{0,S,j}, \tag{A73}$$

where $\lambda_R > 1$ captures the higher underlying default risk of risky borrowers. The portfolio default rate faced by lender $j$ is then

$$\bar{d}_j = \pi_{S,j} d_{S,j}(q_j) + \pi_{R,j} d_{R,j}(q_j). \tag{A74}$$

This extension allows changes in loan rates and approval probabilities to affect not only the allocation of applications across lenders but also the unobserved risk composition of each lender's originated loans.

[41] I set the share of risky borrowers $\mu_R$ to be 0.732 using the complement of the high-creditworthiness population share reported in Agarwal et al. (2024, Table II).

Because borrower type is unobservable, lender $j$ offers one loan rate and one underwriting stringency and uses the endogenous origination weights $\pi_{T,j}$ in both conditions

$$R_j^\ell = \frac{\epsilon}{\epsilon - 1} \frac{C_j}{1 - \kappa_j \bar{d}_j},$$

$$0 = \sum_{T \in \{S,R\}} \pi_{T,j} \left[ \underbrace{-\kappa_j d'_{T,j}(q_j) R_j^\ell}_{\text{reduction in expected default losses}} - \underbrace{s'_j(q_j)}_{\text{marginal underwriting cost}} + \underbrace{\left( (1 - \kappa_j d_{T,j}) R_j^\ell - C_j \right) (1 + \eta) \frac{p'_j(q_j)}{p_j(q_j)}}_{\text{change in approved lending}} \right].$$

For banks, marginal cost is $C_B = R + s_B + \frac{\partial c_B(L_B, E; \nu)}{\partial L_B}$, and for NBFIs, marginal cost is $C_{NB} = R^F + s_{NB}$.

With two types of borrowers, risky borrowers migrate more to the NBFI sector. NBFIs therefore also have a direct incentive to adjust their underwriting stringency because their underwriting choice now depends on the share of risky borrowers in their applicant pool.

**Figure A13.** Effect of higher capital requirements with Two-Type Borrowers

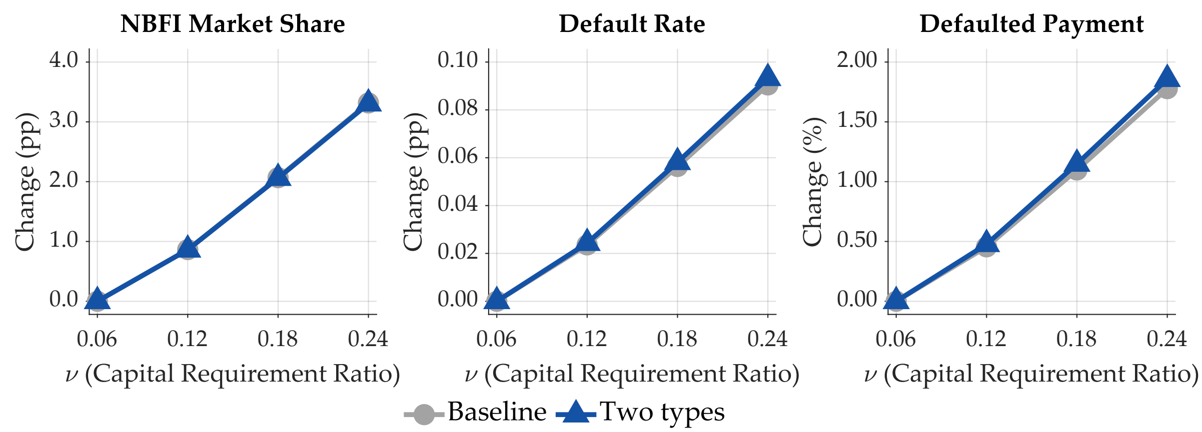



Figure A13 compares the baseline results with those in the two-type borrower economy. Two findings are noteworthy. First, the increases in market share are almost identical across the two economies. Second, aggregate credit risk, in terms of both the default rate and defaulted payments, increases slightly more in the two-type economy. This difference comes from changes in borrower composition and the underwriting response of NBFIs. As more risky borrowers, who are more sensitive to lending rates and have exogenously higher default rates, migrate to NBFIs, NBFIs respond to the change in the composition of their applications and tighten their underwriting stringency. However, this response is not strong enough to offset the increase in the share of risky borrowers. As a result, the average default rate of NBFI loans rises despite tighter underwriting. The market share remains almost identical, but the similar market-share responses conceal different changes in borrower composition and credit risk. Thus, tighter capital requirements increase aggregate credit risk in both economies, with a slightly larger increase in the two-type economy.

### H.2.2. Bank-NBFI Funding Channel

I add a committed bank credit line to the baseline NBFI funding structure, as documented in Jiang (2023); Acharya et al. (2025); Xu (2025). Let $\bar{H}$ denote the total commitment and let $H \leq \bar{H}$ denote the amount drawn by the NBFI. The interest rate on the drawn amount is $R_H = R^F + s_H$, where $R^F$ is the NBFI wholesale funding rate and $s_H$ is the contractual spread. The draw changes the balance sheets of banks and NBFIs and the bank's regulatory exposure according to

$$L_{NB} = F_{NB} + H + E_{NB}, \qquad L_B + H + S_B = D_B + E_B, \qquad \mathrm{RWA}_B = L_B + \omega_D H + c_U(\bar{H} - H).$$

I set $\omega_D = 1$ and use $c_U = 0.50$ for commitments with an original maturity greater than one year.

The credit line allows NBFIs to diversify their funding and reduce their reliance on wholesale funding. I represent this benefit as

$$\mathcal{B}_H(H, L_{NB}) = \theta_H H - \frac{\eta_H}{2}\frac{H^2}{L_{NB}}.$$

Because one dollar of $H$ replaces one dollar of $F_{NB}$, the common funding rate $R^F$ cancels from the draw decision. The NBFI therefore draws the line until the marginal funding benefit equals the additional spread

$$\underbrace{\theta_H - \eta_H \frac{H}{L_{NB}}}_{\text{marginal funding benefit}} = \underbrace{s_H}_{\text{marginal funding cost}}.$$

For an interior draw, this condition gives

$$\frac{H}{L_{NB}} = \frac{\theta_H - s_H}{\eta_H}.$$

I calibrate the facility at $\nu = 0.06$ using three separate moments reported by the Federal Reserve. First, I set $H/L_{NB} = 0.05$ to match the finding that outstanding bank loans to private-credit vehicles are approximately 5 percent of the U.S. private-credit industry. Conditional on $\eta_H$ and $s_H$, this moment determines $\theta_H$. Second, I set $H/\bar{H} = 0.56$ to match the \$44 billion drawn from \$79 billion of revolving commitments to private-credit vehicles. This moment determines the commitment $\bar{H}$ and implies $\bar{H}/L_{NB} = 0.0893$ at the benchmark. Third, I set $R_H^{ann} - 1 = 0.066$ to match the average interest rate on bank facilities to private debt funds. In quarterly units, this gives $R_H = (1.066)^{1/4}$ and determines $s_H = R_H - R^F$. I set $\eta_H = 0.010$ as the curvature governing how the marginal funding benefit declines with the draw share.

For the bank, the drawn amount earns $R_H$ but replaces a safe asset earning $R$ and increases the capital cost through $\text{RWA}_B$. The calibrated facility produces a positive net margin for the bank at $\nu = 0.06$. I therefore treat $\bar{H}$ and $s_H$ as the terms of an existing contract. After $\nu$ changes, the NBFI chooses $H$, while the bank honors any draw up to $\bar{H}$. Thus, $H$ is the only additional endogenous choice after the contract date.

**Figure A14.** Effect of higher capital requirements with Bank-NBFI Credit Line

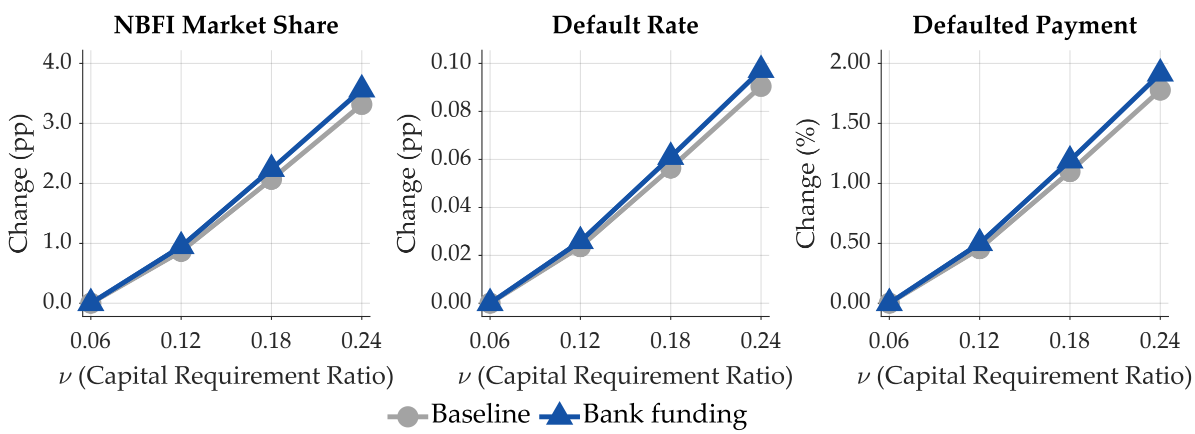



Figure A14 compares the baseline with the committed bank credit line. When the capital requirement rises, banks reduce lending and borrowers shift toward NBFIs. The committed line lowers the effective funding cost of NBFIs by replacing part of their wholesale funding with a more stable funding source. NBFIs can therefore absorb more of the lending displaced from banks. As a result, the increases in their market share, the aggregate default rate, and total defaulted payments become larger.

## H.3. Loan Sales and Balance-Sheet Retention

I relax the baseline assumption that banks retain all newly originated loans. Let $O_B$ denote total bank originations, $H_B$ retained loans, and $X_B$ sold loans. The allocation of originated loans and the bank's regulatory exposure are

$$O_B = H_B + X_B, \qquad \mathrm{RWA}_B = H_B + \rho_X X_B.$$

A retained loan carries full regulatory exposure, whereas a sold loan leaves the fraction $\rho_X$ of that exposure with the bank.

I represent the cost of selling loans as

$$\Phi_X(X_B) = m_X X_B + \frac{\zeta_X}{2\bar{O}_B}\left(X_B - \bar{X}_B\right)^2, \qquad \bar{X}_B = \bar{x}_B \bar{O}_B.$$

The model does not determine a separate secondary-market price or investor demand. Instead, $\Phi_X(X_B)$ summarizes the cost of placing loans outside the bank's balance sheet. The marginal sale cost is

$$\Phi_X'(X_B) = m_X + \frac{\zeta_X}{\bar{O}_B}\left(X_B - \bar{X}_B\right).$$

Retaining one additional loan requires funding at the return $R$ and creates one unit of regulatory exposure. Selling the loan incurs the marginal sale cost and leaves the residual exposure $\rho_X$. The bank therefore chooses $X_B$ according to

$$R + c_B^{\mathrm{RWA}} = \Phi_X'(X_B) + \rho_X c_B^{\mathrm{RWA}},$$

or equivalently,

$$\Phi_X'(X_B) = R + (1 - \rho_X) c_B^{\mathrm{RWA}}.$$

The bank sells loans until the marginal sale cost equals the funding cost and capital cost avoided by not retaining them.

At $\nu = 0.06$, I impose the benchmark sale share $\bar{X}_B/\bar{O}_B = 0.40$ and choose $m_X = R + (1 - \rho_X) c_B^{\mathrm{RWA}}$ so that the benchmark allocation satisfies the sale condition. I set $\rho_X = 0.20$ as a maintained assumption about the residual regulatory exposure of sold loans. I set $\zeta_X = 0.154$ to govern how rapidly the marginal sale cost increases when sales move away from their benchmark level.

**FIGURE A15.** Effect of higher capital requirements when Banks can sell Loans

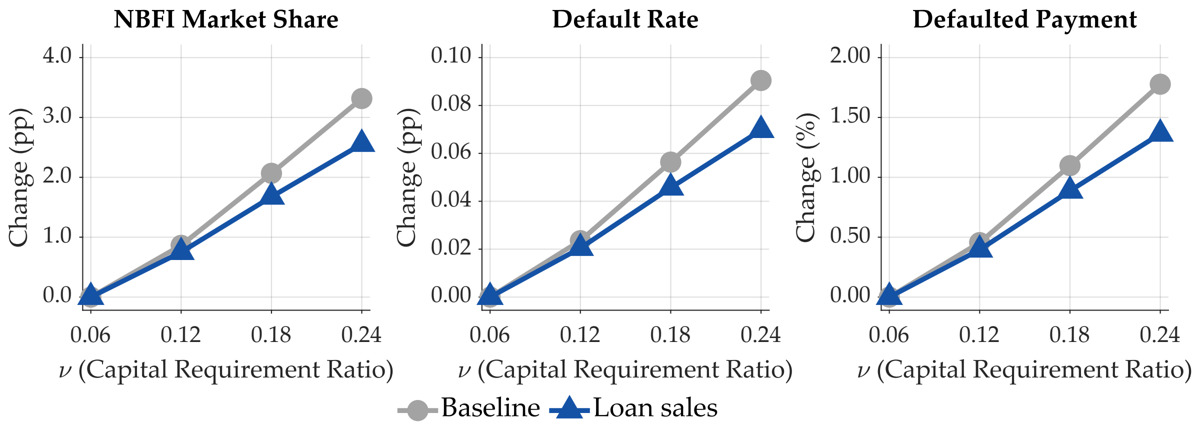



Figure A15 shows the results. The effects of capital regulation on market share and aggregate credit risk are mitigated. The reason is that when the capital requirement rises, the marginal capital cost of retaining loans increases. Banks therefore sell a larger share of their originations and reduce their regulatory exposure. This margin limits the contraction in bank lending and weakens the reallocation of credit toward NBFIs. The aggregate default rate and defaulted payments still increase, but the increases are smaller than in the baseline without loan sales.

### H.3.1. Reapplication after Bank Rejection

I relax the baseline assumption that denied applicants do not submit another application. Applicants who are denied, especially by banks, draw a search cost and make one additional application to an NBFI. Some borrowers rejected by banks still satisfy the NBFI underwriting cutoff and can obtain loans under the NBFI rules. I assume that borrowers who fail the NBFI cutoff cannot obtain bank credit, so reapplication occurs only from banks to NBFIs. This is because applicants who are rejected by NBFIs cannot obtain loans from banks in the model. Finally, I do not allow additional applications.

Let $c$ denote the search cost and $V$ the expected benefit from an NBFI loan conditional on bank rejection. An applicant reapplies when this expected benefit exceeds the search cost. When $V > 0$, the fraction of bank-denied applicants who reapply is

$$\rho = \Pr(c \leq V). \tag{A75}$$

When $V \leq 0$, there is no reapplication. Search costs are independent of creditworthiness and application preferences. Applicants observe that they were rejected by a bank but do not observe their exact creditworthiness when deciding whether to reapply. The search cost is incurred upon submitting the second application even if the NBFI rejects it. I treat this cost as nonpecuniary and include it in borrower utility.

I parameterize search costs using the mean additional-search cost estimated by Agarwal et al. (2024), which corresponds to an annual interest-rate spread of 29.7 basis points. I map these costs into the present value of additional mortgage payments. This conversion is used only to express the search cost in model units and does not add a spread to the loan rate paid by borrowers.[42] The reapplication rate is determined in equilibrium. As the search cost becomes sufficiently large, the model becomes isomorphic to the baseline, in which reapplication is absent.

Because reapplication is an additional decision made only after a bank rejection in the model, reapplication changes the composition of the NBFI applicant pool. Let $p_B = p_B(q_B)$ and $p_{NB} = p_{NB}(q_{NB})$ denote approval probabilities for initial applicants. Then, the probability that an applicant rejected by a bank still satisfies the NBFI cutoff is

$$r = \frac{p_{NB} - p_B}{1 - p_B}. \tag{A76}$$

Then, let $s_R$ denote the share of NBFI applications coming from bank-denied borrowers. The observed NBFI approval rate is then

$$\widetilde{p}_{NB} = (1 - s_R)p_{NB} + s_R r. \tag{A77}$$

The first term comes from initial NBFI applicants and the second captures the contribution from reapplicants. The NBFI default rate is also determined by the composition of originated loans. NBFIs therefore choose loan rates and underwriting standards taking both groups into account. A reapplication creates an additional application record but does not increase the amount the borrower is allowed to borrow.

I introduce reapplication while holding all other parameters at the baseline values. I recompute the steady-state equilibrium as the capital requirement increases from 6 to 24 percent. Each curve is measured relative to the steady state of the same economy at $\nu = 0.06$.

[42] I convert the interest-rate spread into the present value of the extra payments a borrower would make on a thirty-year mortgage. I use the baseline NBFI loan rate and the borrower discount factor, assuming no prepayment or refinancing. Search costs are set so that their interest-rate equivalents average 29.7 basis points. This calculation is only used to measure the search cost, and loans in the model still last one quarter.

**FIGURE A16.** Effect of Higher Capital Requirements with Reapplication: Baseline Parameters Held Fixed

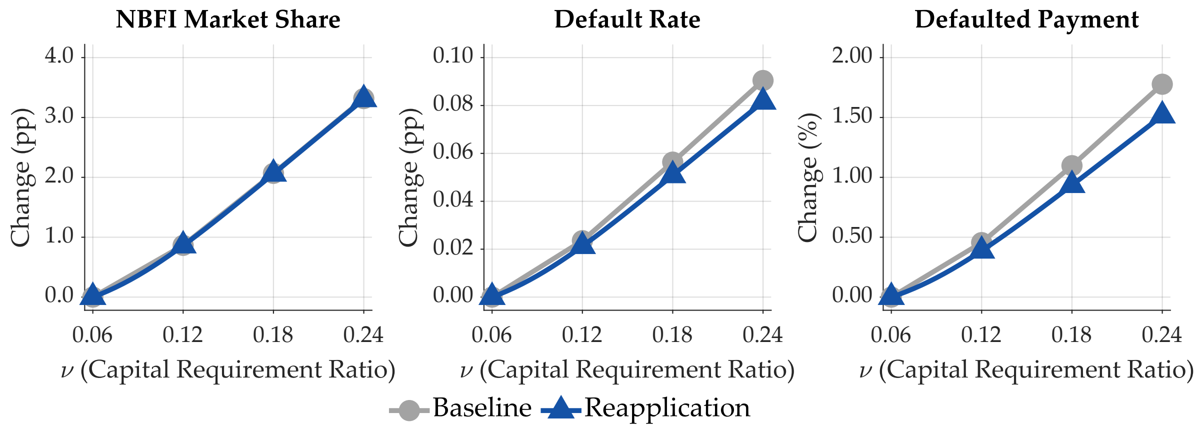



Figure A16 shows that reapplication reduces the aggregate credit risk responses but does not overturn the results. When the capital requirement increases from 6 to 24 percent, the annualized default rate rises by 0.065 percentage points and total defaulted payments rise by 0.79 percent. These increases are 7.2 and 24.2 percent smaller than in the baseline, respectively.

The reason is that some borrowers who would otherwise remain unfunded after the first application can obtain NBFI credit after a bank rejection, even before regulation tightens. A subsequent shift in initial applications toward NBFIs therefore brings *fewer* previously unfunded borrowers into the originated loan pool compared to the baseline. Under this setting, the model generates a quarterly reapplication rate among bank-denied applicants of 25.5 percent at $\nu = 0.06$, rising to 26.1 percent at $\nu = 0.24$. The model reults show that the realized reapplication rate is 69.3 percent, broadly comparable to the 64.1 percent SCF-based proxy. This comparison supports the quantitative plausibility of the cost calibration and shows that the main results hold even with substantial reapplication.

# Appendix I. Bank Capital and Expected Crisis Costs

I conduct an illustrative welfare exercise to account for a benefit of bank capital that is absent from the baseline model. Higher bank capital reduces the probability of a financial crisis and therefore its expected cost. I use the relationship between bank capital and the annual crisis probability reported in Table 3 of Firestone et al. (2017). I utilize this relationship to the model's bank equity-to-loan ratio, $k_t = E_{B,t}/L_{B,t}$, and interpolate the crisis probability.

I set the cost of a crisis to 19% of annual output, following the case without permanent output effects in Basel Committee on Banking Supervision (2010). The expected quarterly cost is therefore

$$\Gamma_t = 0.19(4\bar{Y})\left[1 - (1 - p_A(k_t))^{1/4}\right],$$

where $p_A(k_t)$ is the annual crisis probability and $\bar{Y}$ is quarterly output in the benchmark economy. I introduce this cost into the saver budget and the aggregate resource constraint and solve the equilibrium again. Welfare includes consumption and labor for both households and liquidity services for savers.

I then compare three cases, the model without the added crisis cost, the model with this cost, and a comparison economy with the same cost specification but without endogenous borrower default that the model highlights. In the third case, screening costs and screening-related rejection are also removed.

In this back-of-the-envelope calculation, the reported welfare measure is highest on the examined grid at capital requirements of 0%, 9%, and 10% in the three cases, respectively. This result illustrates how the benefit of preserving bank capital can support positive capital requirements while credit losses offset part of that benefit.