# Bank Credit Supply: Asymmetric Drivers and Credit Outcomes*

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**Abstract**

Bank credit supply is central to economic activity yet difficult to measure: it is unobservable, multidimensional—encompassing standards, prices, and non-price terms—and potentially confounded by demand-related developments. We construct a novel comprehensive bank-quarter level credit supply index using the Survey of Loan Officer Opinion Survey (SLOOS) and link it to balance-sheet (Call Reports) and loan-level data (Y-14Q) to examine patterns for how and why banks adjust credit supply. We document a striking asymmetry: banks tighten credit in response to risk concerns (sharply reducing originations with minimal rate increases), and ease in response to competitive pressures, predominantly through rate cuts. We develop a quantitative general equilibrium model of bank lending where banks choose loan rates and screening intensity, learning about borrower pool quality from past performance while facing monopolistic competition and capital constraints. The model replicates the observed asymmetric patterns and provides a framework for quantifying the contribution of distinct supply mechanisms to aggregate credit dynamics.

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# 1 Introduction

Supply-driven contractions in bank credit can have large, adverse effects on macroeconomic outcomes, including employment and output (see, for example, Alfaro et al. (2021); Chodorow-Reich (2014); Herkenhoff (2019)). These effects arise because tighter credit conditions restrict firms' access to external finance, limiting their ability to fund working capital and investment (see for example, Bassett et al. (2014) and Lown and Morgan (2006)). Measuring and studying bank credit supply, however, is challenging. Credit supply is not directly observable, and it is multidimensional—encompassing who receives credit, how much credit is extended, and at what terms and prices. Moreover, observed loan outcomes reflect both supply and demand forces which are difficult to disentangle. Understanding why banks adjust supply, and along what margins credit availability changes, is therefore important for understanding transmission of bank credit supply to the real economy.

This paper studies bank credit supply, the forces driving its adjustment, and the margins along which it changes. We focus on four related questions. First, how can credit supply be measured in a way that accounts for the multiple and simultaneous lending decisions embedded in banks' policy choices, including loan approvals, pricing, collateral requirements, covenants, and other terms? Second, what leads banks to tighten or ease lending policies, and what role do performance expectations, competitive pressures, and balance sheet capacity play in loan contract decisions? Third, when banks change lending policies, do these adjustments primarily affect loan prices, origination volumes, or the observable composition of newly originated loans? Finally, what economic mechanisms explain the observed drivers and outcomes of credit supply adjustments, and what do they imply for aggregate credit dynamics?

We approach these questions both empirically and theoretically. Empirically, we combine confidential microdata on banks' self-reported changes in lending policies from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) with lending outcomes from Call Report and Y-14Q data. We use SLOOS data to construct a bank-quarter level tightening index measuring broad changes in the stringency of lending policies based on responses to questions about changes in loan standards, and a variety of price and non-price terms for C&I loans. This approach captures the richness of banks' credit supply decisions in a single index, and allows us to assess how changes in credit supply, broadly considered, relate to lending outcomes.

We first document that changes in lending policies have a strong common component. Principal-components analysis of SLOOS terms reveals that most of the variation in terms can be accounted for by a single factor net tightening. This first principally component essentially measures the share of terms banks report tightening net of the share of terms banks report as having eased. The second component reflects whether banks adjust price or non-price terms, suggesting that the next important dimension of credit-supply adjustment (after whether banks broadly tighten or ease) is whether banks change their exposure to or compensation for credit risk. This motivates a framework that treats credit supply as multidimensional and distinguishes price adjustments from changes in standards and other non-price terms.

We then use loan-level data from Y-14Q to validate that this index indeed captures changes in credit supply. We focus our analysis on the cross-section, evaluating trends for banks that tighten credit supply relative to banks whose lending policies are unchanged. Exploiting within-quarter variation in credit supply across banks controlling for reported loan demand allows us to more cleanly separate the effects of bank credit supply from demand and aggregate macroeconomic conditions. Indeed, we show that tighter lending policies are associated with higher loan rates and lower loan origination volumes, consistent with the index successfully capturing supply-related developments. Lastly, we find only a modest increase in loan-rate spreads, about 8 basis points for a bank that tightens along all queried terms, but a much larger decline in C&I loan originations, about 8 percent. Thus, the main adjustment to tightening occurs through quantities rather than prices, highlighting the importance of an extensive or approval margin.

We next investigate the determinants of changes in credit supply, using both Call Reports and Y14-Q data. Banks' self-reported reasons for changing C&I loan standards or terms in the SLOOS point to a stark asymmetry in why banks adjust lending policies; Banks predominantly tighten supply due to performance concerns but ease due to competitive pressures from other lenders. This asymmetry is borne out in the data. Banks tend to experience weaker loan performance (i.e., rising net charge-offs or nonperforming loan rates) after tightening lending policies, consistent with them acting in anticipation of performance strains. Banks also experience weak loan growth prior to easing policies, consistent with them counteracting weak credit flows due to competitive pressures.

We also find an asymmetry in the margins of adjustment. Risk-driven tightening is broad-based, affecting both price and non-price terms. Competition-driven easing, by contrast, is concentrated more strongly in price terms. Again, these patterns are seen in both banks' self-reported reasons for changing policies and in patterns observed in the data. Specifically, banks that report that competition is an important reason to ease disproportionately report easing price terms, while those that cite risk factors as important reasons for tightening policies tighten on both price and non-price dimensions. In the data, banks that tighten lending policies experience a particularly sharp drop in originations, consistent with non-price terms (namely, approvals) becoming more stringent. In contrast, banks that report easing lending policies in SLOOS observe a comparatively larger change in loan pricing than in lending volumes.

To rationalize these empirical findings, we develop a quantitative model of bank lending with heterogeneous banks, informational frictions, financial frictions, and imperfect competition among banks and between banks and nonbanks. The model builds on Dempsey (2025), extending it to study how individual banks optimally adjust screening, loan approvals, pricing and financing in response to borrower risk, competitive pressures, and balance sheet constraints.

Banks differ in net worth, demand conditions or market shares and applicant pool quality. They choose loan rates and screening intensity before fully observing the current quality of their applicant pool. This allows the model to distinguish the price margin from the standards or approval margin: a bank can respond to risk by screening more intensively rather than raising rates, while it can respond to competition by lowering rates without necessarily changing screening as much. Screening improves the composition of approved loans by removing bad applicants, but it is costly and reduces approvals. Once loan outcomes are realized, banks choose deposits and equity subject to budget constraints, regulatory capital requirements, and costly equity issuance. This connects credit supply adjustments to bank balance-sheet management, capturing the idea that banks cannot expand lending without funding and capital to support it.

A key friction in the model is that bank lending policies are chosen under uncertainty. Banks set rates and screening intensity before they know the exact current realization of applicant-pool quality. This captures the idea that, in practice, underwriting standards are set using expected borrower quality, recent performance, and macroeconomics and industry information. Banks observe signals from past realized outcomes, but they do not directly observe whether performance reflects a persistent deterioration in the borrowers they attract or transitory noise. They therefore update beliefs about persistent borrower-pool quality over time, and these beliefs shape future screening, approvals, and credit supply. Screening affects both loan volumes and expected returns by shaping the composition of borrowers. Its value also depends on banks' financial positions: more constrained banks have less capacity to absorb losses and may therefore adjust lending standards more aggressively in response to adverse shocks.

The model generates the empirical asymmetries through distinct mechanisms. Risk-driven tightening operates through beliefs and screening: when banks become more pessimistic about borrower quality, they increase screening, approve fewer marginal borrowers, and reduce originations, even if loan rates rise only modestly. Competitive pressure works primarily through the price-volume tradeoff: when borrowers can substitute across banks or toward nonbank lenders, banks have an incentive to reduce rates or ease price terms in order to preserve loan volume and market share. Balance-sheet constraints amplify these responses by limiting banks' ability to absorb losses or expand lending when net worth is weak.

The model is disciplined by the empirical facts documented in the paper. Deterioration in loan performance raises the expected cost of lending and increases the value of screening. This can lead banks to tighten, especially when capital constraints bind, consistent with the observed risk-driven tightening episodes. In contrast, increases in competitive pressure compress markups and induce easing and may be weaker when balance-sheet constraints are binding. The calibrated model therefore provides a framework for quantifying the relative importance of screening, pricing, learning, competition, and financial constraints in credit-supply dynamics.

In the quantitative part of the paper, we first calibrate the model at a quarterly frequency, targeting moments related to banks' balance-sheet constraints, lending behavior, and credit market structure. Our approach ensures that the model reproduces both aggregate credit conditions and cross-sectional variation in lending outcomes. Second, we describe the model's mechanics and assess its performance along key cross-sectional dimensions and validate the model by revisiting the main empirical findings through a set of simulation exercises. Specifically, we study banks' optimal lending and screening responses to adverse realizations of loan returns and to exogenous contractions in loan demand that increase competitive pressure. Finally, we use the calibrated model in counterfactual experiments to decompose credit-supply dynamics and answer questions the data cannot answer directly. In particular, we ask what fraction of a tightening episode reflects screening rather than pricing; how learning and borrower-risk beliefs affect credit provision; how important capital constraints are for translating losses into lower lending; and how bank and nonbank competition changes bank rates and market shares.

In the last part of the paper, we illustrate the usefulness of our framework through the banking stress episode of March 2023. While aggregate measures indicate a broad contraction in credit supply, extending our bank-level index to this period reveals pronounced cross-sectional heterogeneity, with regional banks tightening substantially more than large banks. Interpreted through the model, this divergence reflects differences in balance-sheet vulnerabilities and funding pressures, which shape banks' incentives to adjust screening and lending policies during stress episodes. Together, the index and the model provide a coherent account of the uneven contraction in credit supply observed during the SVB episode.

**Related literature** We contribute to two main strands of literature. First, we add to empirical work examining the implications of credit supply. Previous work used VAR-based identification strategies to study the effects of changes in aggregate lending standards, controlling for loan demand (Lown and Morgan, 2002, 2006; Cappiello et al., 2010; Ciccarelli et al., 2015). Bassett et al. (2014) conducts similar analysis, but using bank-level microdata to purge standards measures of macroeconomic or bank-specific factors potentially correlated with demand. This work demonstrates that adverse credit supply shocks result in significant declines in loan commitments and GDP, and a widening of credit spreads.

We build on this work in a couple of ways. First, we broaden the measurement of credit supply to incorporate information on various dimensions that banks might adjust beyond just lending standards (including loan pricing, size, and covenants). We find that this broader measure of supply is more predictive of credit growth than standards alone. Second, we analyze changes in supply at the bank-level rather than in aggregate. By combining bank-specific responses about changes in credit policies with bank- and loan-level outcomes from the Call Reports and Y-14Q, respectively, we are able to examine in greater detail how and why banks adjust credit supply. Furthermore, by using within-quarter variation in supply conditions, we are able to more cleanly separate the effects of changes in credit supply from macroeconomic drivers of loan outcomes.

Second, we contribute to the literature developing quantitative models of banking industry dynamics, including recent work by Corbae and D'Erasmo (2021) and Dempsey (2025), as well as related research in consumer credit (e.g., Chatterjee et al., 2023). Together, these papers expand macro banking models: Corbae and D'Erasmo (2021) emphasizes how bank dynamics interact with regulation, showing that industry composition and risk are jointly determined, while Dempsey (2025) highlights the interaction between banks and non-bank finance, demonstrating that regulation must account for substitution across lenders. Collectively, they show that capital regulation has both structural (industry-level) and systemic (macro-financial) effects, moving beyond single-bank or representative-bank frameworks toward models incorporating heterogeneity, competition, and endogenous responses.

We build on this body of work by adopting a heterogeneous bank model that incorporates industry dynamics in the spirit of Corbae and D'Erasmo (2021) and competition from non-banks as in Dempsey (2025), while, like these studies, grounding macro outcomes in micro-level data. Unlike these papers, which focus on capital regulation, our work emphasizes bank lending policies. In that vein, our primary contributions relative to this literature are to account for the multiple dimensions along which banks may adjust supply, including both pricing and approval margins, and the incorporation of learning mechanics that is disciplined by micro data.

# 2 Empirical Analysis

In this section, we combine survey data on banks' lending standards with portfolio-level data on loan performance and origination activity to address three key questions about credit supply. First, how do banks adjust credit supply (i.e., what terms change)? Second, why do banks change supply (e.g., competitive pressures, credit strains, etc.)? Third, what happens when banks do adjust supply (e.g., how does the quantity, price, or composition of credit change)?

To address these questions empirically, we proceed as follows. Section 2.1 introduces the three primary data sources we use in our analysis. Section 2.2 discusses *what terms* banks self-report as changing and how we use this information to construct credit supply measures. Section 2.3 discusses banks' self-reported *reasons* for changing supply. Section 2.4 links SLOOS responses to lending outcomes to validate the qualitative, self-reported responses and quantitatively examine the *response of loan outcomes* such as lending volumes.

## 2.1 Data sources

Our analysis combines data from three different sources: (i) reported changes in loan terms and standards from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS); (ii) bank balance sheet data from the Consolidated Reports of Condition and Income (Call Reports); and (iii) loan level data from Capital Assessments and Stress Testing information collection (Y-14).

Throughout our analysis, we focus on Commercial and Industrial (C&I) loans because responses to those questions have the longest time series (dating back to 1990), and provide the most detail about changes in lending conditions (including changes in various loan terms and reasons for changing terms and standards). We will show that many of the most common reasons for changing C&I terms or standards pertain to more general concerns about the economic outlook or changes in risk tolerance that would pertain to other loan categories as well. We indeed find that banks reporting tighter C&I credit policies observe declines in the size of their entire loan portfolio, not just for C&I loans.

**SLOOS** The SLOOS is a quarterly survey of banks which inquires about changes in supply or demand for various categories of loans. A typical survey has about 70 banks responding, and these banks generally account for about 70% of the total assets of domestically chartered financial institutions in the U.S., and so the respondents account for a meaningful swath of total credit supply. We use SLOOS to construct our primary bank-quarter-level credit supply measure and to document banks' self-reported reasons and methods for adjusting lending policies.

While aggregated and anonymized survey response data from the SLOOS is publicly available, we use the confidential, de-anonymized, microdata which allows us to link responses to balance sheet and loan origination data by bank and quarter. This crucially allows us to study the drivers and implications of credit supply at the bank level, whereas most existing work focuses on fluctuations in aggregate credit (see, for example, Lown and Morgan, 2006; Bassett et al., 2014).

The SLOOS has asked banks about changes in lending standards and various loan terms for C&I loans on a quarterly basis since 1990. An example question is: "Over the past three months, how have your bank's credit standards for approving applications for C&I loans or credit lines – other than those to be used to finance mergers and acquisitions – to large and middle-market firms and to small firms changed?"[1] Banks respond on a Likert scale from 1 to 5: 1 (2) means "eased considerably (somewhat)," 3 means "basically unchanged," and 4 (5) means "tightened somewhat (considerably)." Questions in this vein are asked about numerous aspects of banks' C&I lending policies: (i) standards for approval; (ii) maximum sizes of credit lines; (iii) maximum maturity of credit lines; (iv) costs of credit lines; (v) loan spreads; (vi) risk premia; (vii) loan covenants; (viii) collateralization requirements; and (ix) the use of interest rate floors.

**Call Reports** The Call Reports provide quarterly information on bank balance sheets for the full universe of US banks. This includes a wealth of information on (among other things) banks' loan portfolios and loan performance. The key variables of interest are merger-adjusted loan growth, and changes in nonperforming loan rates or net charge off rates.

The merger adjusted change in a balance sheet item $y$, for a bank $b$, in quarter $t$ is computed by as the difference between $y_{b,t}$ and $\sum_{b' \in P_{b,t}} y_{b',t-1}$ where $P_{b,t}$ is the set of predecessor banks for $b, t$ ($P_{b,t} = \{b\}$ absent mergers). Growth over longer horizons are computed by cumulating quarterly merger-adjusted changes over the desired time horizon. We are loose with notation for the sake of readability, and express regression specifications using the notation that would apply to a bank that has no merger over the relevant time horizon. For example, the growth in C&I balances over horizon $h$ is expressed as $\ln(\text{C\&I Balance})_{b,t+h} - \ln(\text{C\&I Balance})_{b,t-1}$, even though the variable strips out any growth over the horizon attributable to mergers.

[1]Banks are asked separately about standards and terms for C&I loans to small firms and to large and middle-market firms, as well as about C&I loans versus other classes of loans. We use responses about loans to large firms as the survey disproportionately samples large banks, who lend more to larger firms. Furthermore, the Y-14Q data covers commitments over $1 million, making the data more reflective of loans to larger firms.

**Y-14** The Y-14 provides detailed loan-level data on the portfolios of banks with at least \$100 billion in total consolidated assets.[2] This data is collected by the Federal Reserve for the purpose of conducting the Comprehensive Capital Analysis and Review (CCAR), the Fed's annual stress tests of the largest banks. Schedule H.1 of the Y-14Q provides quarterly data on banks' holdings of C&I loans with committed exposures above \$1 million.

For our purposes, Y-14 augments the Call Reports in two key ways. First, the data includes detailed information on loan terms and borrower characteristics. Second, it allows us to separate a bank's newly originated loans from the rest of its portfolio. Consequently, it allows us to measure the effect of a change in credit supply specifically for new originations, and provide more detail on changes in the composition of credit over time. The primary cost is that it is available for a shorter period of time (since 2012 rather than 1990) and for a smaller sample of banks (≈25 of the ≈70 SLOOS respondents).

## 2.2 How do banks adjust credit supply

**What terms do banks change?** As discussed above, the measurement of credit supply at the bank level is complicated by multi-dimensionality; lenders may adjust lending policies on intensive and extensive margins, as well as changing numerous potential price and non-price terms. Here we discuss which dimensions banks report changing, and how to parsimoniously measure credit supply in order to study its implications.

We start by using principal components analysis (PCA) to characterize changes in the various terms banks are asked about. Specifically, for every question $j$ we construct a categorical variable $\text{Net Tighten}_{b,t,j}$ which takes a value of 1 if bank $b$ reports tighter terms at time $t$, -1 if the bank reports easier terms, and 0 if the bank reports terms as unchanged. "Terms" here is defined broadly to also include lending standards (see the SLOOS paragraph in Section 2.1 for a list of the queried terms).[3]

Figure 1 plots the loading on each term for the first and second principal component. The main takeaway from the loading plot is that terms tend to all move together. The loading on the first principal component is nearly identical for each variable, making the first principal component essentially reflect the average net tightening across the queried terms. This first principal component, which can be thought of as a general credit supply tightening factor, accounts for about half of the overall variance in banks' self reported changes in terms. The strong co-movement between the various terms may partly reflect the fact that these dimensions are not always conceptually distinct. For example, if a bank requires a greater rate premium to originate high loan-to-value (LTV) loans, this changes the constellation of terms so that banks could be interpreted as requiring higher spreads, lower loan sizes, or more collateral (each holding the remaining two terms constant). Consequently, it can be more informative to think about whether a bank is tightening credit overall

[2] The Economic Growth, Regulatory Relief, and Consumer Protection Act (S. 2155) increased the threshold from \$50 billion to \$100 billion, so a couple of somewhat smaller banks are available earlier in the sample.

[3] We do not distinguish between the "considerably" and "somewhat" modifiers as banks rarely report changing standards "considerably."

rather than to isolate a specific dimension.

The second component distinguishes whether banks are adjusting price or non-price terms; loadings are positive for non-price terms (maximum loan size, collateral, maximum maturity, covenants and standards) and negative for price terms (risk pricing, cost of credit lines, spreads, and rate floors). Namely, the second most important dimension appears to be whether banks are adjusting their exposure to credit risk or their compensation for it. This price vs. non-price distinction is somewhat secondary to the question of whether banks are tightening or easing—the second principal component only accounts for about 10 percent of the variance—so we predominantly focus on the direction with which credit supply is changing, rather than the specific terms changing.

Figure 1: **Loadings Plot for PCA of C&I Terms**


**Notes:** This figure plots the loadings of the first and second principal component when performing PCA on responses to the various questions about changes in credit standards and loan terms. The loadings for the first principal component are on the x-axis, and loadings for the second principal component are on the y-axis.
**Source:** SLOOS.

**Measuring Credit Supply** One complication in using these principal components to directly measure supply changes is that the set of terms banks are asked about varies somewhat over time, with questions about risk pricing, maximum maturity, and interest rate floors getting added at staggered time points later in the sample. To accommodate changes in the set of terms over time, we instead measure credit supply changes by average net tightening across queried loan terms:

$$\text{Net Tightening index}_{b,t} = \frac{1}{|J_t|} \sum_{j \in J_t} \text{Net Tighten}_{b,t,j},$$

where $J_t$ is the set of terms available in quarter $t$. Given that the loadings of the first principal component are nearly identical, this measure approximates the first principal component, but provides flexibility for the set of terms to change.

This index can be decomposed in various ways to provide additional color on how banks are adjusting credit supply. To examine whether tightening in terms have asymmetric effects to easing, we decompose this index into a tightening and easing index:

$$\text{Net Tightening index}_{b,t} = \underbrace{\frac{1}{|J_t|}\sum_{j\in J_t}\text{Tighten}_{b,t,j}}_{\text{Tightening index}_{b,t}} - \underbrace{\frac{1}{|J_t|}\sum_{j\in J_t}\text{Ease}_{b,t,j}}_{\text{Easing index}_{b,t}},$$

where $\text{Tighten}_{b,t,j}$ and $\text{Ease}_{b,t,j}$ are indicators for whether banks tighten or ease term $j$, respectively.

A second decomposition, motivated by the principal components analysis, is to decompose the index into whether banks are tightening on net with respect to price or non-price terms:

$$\text{Net Tightening Index}_{b,t} = \frac{|J_t^{NP}|}{|J_t|}\underbrace{\frac{1}{|J_t^{NP}|}\sum_{j\in J_t^{NP}}\text{Net Tighten}_{b,t,j}}_{\text{Non-price index}_{b,t}} + \frac{|J_t^{P}|}{|J_t|}\underbrace{\frac{1}{|J_t^{P}|}\sum_{j\in J_t^{P}}\text{Net Tighten}_{b,t,j}}_{\text{Price index}_{b,t}},$$

where $J_t^P$ and $J_t^{NP}$ partition the sample of questions into those pertaining to price and non-price terms respectively.

This work builds on a large existing literature using SLOOS responses to measure credit supply. For example, Lown and Morgan (2006) and Bassett et al. (2014) both construct aggregate measures of the shares of banks tightening standards and show that those indexes are predictive of economic activity. Our credit supply measures differ on two important dimensions. First, we focus on the cross-section of banks rather than the time series. In other words, we ask what happens when banks tighten relative to other banks, instead of what happens when banks are tightening in aggregate. This focus complements the theoretical work, which focuses on banks' response to idiosyncratic developments rather than aggregate shocks. Second, instead of focusing solely on lending standards, we measure credit supply based on the full array of standards and terms that banks report about in the SLOOS. We demonstrate that this broader measure of credit supply is useful; the tightening index is more predictive of subsequent changes in loan balances than reported changes in standards alone.

Appendix A.1 provides additional analysis pertaining to the credit supply measure. Panel (a) shows that the average of the Net Tightening index across banks moves closely with the net share of banks tightening standards. The value of the Net Tightening index predominantly is the cross-section; while the net change in standards takes on three discrete values, the Net Tightening index provides a more granular measure of changes in credit supply and gives a sense of the intensity of tightening. Panel (b) shows that the Net Tightening index and the Price and Non-price indexes are nearly identical to principal components-based measures of changes in terms. The Net Tightening index is nearly perfectly correlated with the first principal component and the price and non-price indexes are nearly perfectly correlated with the associated first two principal components with varimax rotation.[4] Panel (c) presents a scree plot showing the sharp drop-off in the variance explained by the second principal component, justifying our focus on broad tightening rather than the specific terms banks report changing. Panel (d) presents a loadings plot excluding the three terms that were added to the survey after 1990, and shows that the same patterns hold for the longer time series (i.e., the first principal component measures broad tightening, and the second tightening in price vs. non-price terms).

### 2.3 Why do banks change lending policies? Evidence from SLOOS self-reports

Armed with a composite measure of shifts in loan supply at the bank level, we now examine the drivers of changes in loan supply. One of the key contributions of our empirical analysis is to link qualitative survey responses from the SLOOS to concrete, quantitative financial variables from the Call Reports and Y-14Q data (see Section 2.4 below). Banks' self-reported reasons for adjusting standards, however, provide a useful benchmark and frame for this analysis.

**What factors are important in credit supply decisions?** Every SLOOS since 1995, when banks reported tightening or easing at least one C&I loan term, they were asked how important various reasons were for the change. These reasons include changes in (i) capital positions, (ii) liquidity positions, (iii) tolerance for risk, (iv) the favorability/uncertainty of the economic outlook, (v) industry-specific problems, (vi) secondary market liquidity, (vii) the aggression of competition from other lenders, and (viii) concern about legislation, supervision or accounting standards.

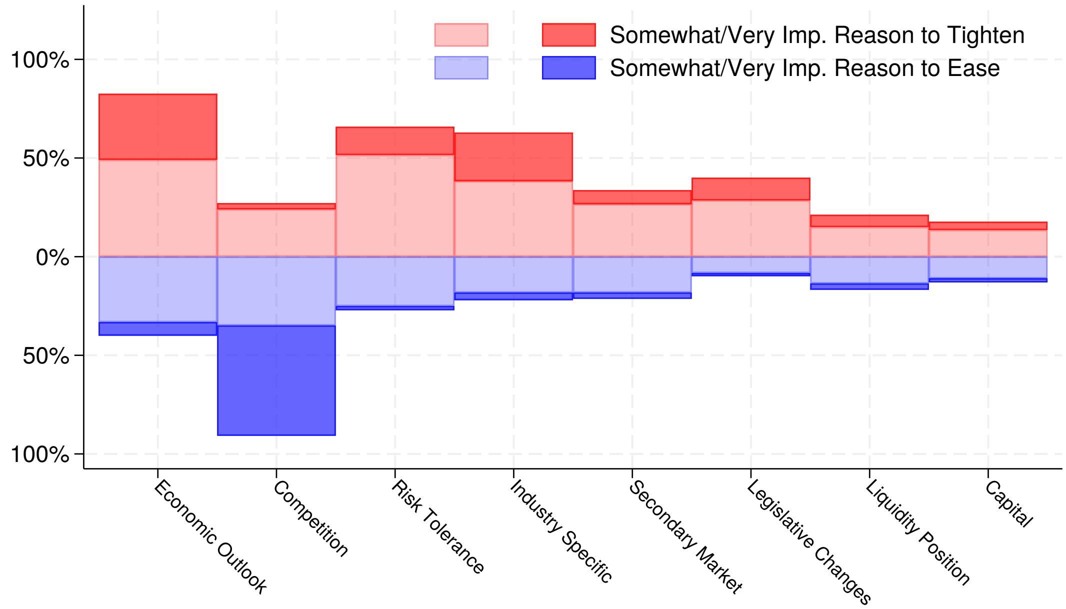
Figure 2 plots the share of banks citing a given factor as a reason for tightening (red bars, top half) or easing (blue bars, bottom half) credit supply. The red bars in the top half of Figure 2 reveal that, upon *tightening* credit supply, loan officers tend to cite risk factors (e.g. risk tolerance, industry specific problems, and changes in the favorability of the economic outlook) as the most important drivers. This is expected: since increased credit risk may reflect a worsening of the underlying pool of borrowers, it would be optimal for banks to tighten supply in response to this. This holds true for either realized increases (e.g. rising C&I loan charge-offs or nonperforming loan rates) or anticipated increases (e.g. rising default expectations).

By contrast, the blue bars in the bottom half of the figure demonstrate that the predominant reason banks *ease* credit is an increase in competition from other lenders. This too, is intuitive: if intense competition from other lenders causes a bank to lose market share, it might be optimal to ease credit to stimulate lending.

**How do reasons for changing supply relate to the terms changed?** These different motivations for changing credit supply also relate to banks' decisions about *how* to change credit supply.

[4] Varimax rotation rotates components so that instead of components being ordered by maximal variance, they are chosen for a simple structure (which in this scenario results in components that clearly align with tightening in price and non-price terms).

Figure 2: **Self Reported Reasons for Changing C&I Terms or Standards**




**Notes:** This figure plots banks' self reported reasons for changing terms or standards. The height of the bars above the x-axis shows the share of banks tightening terms or standards that cite a particular reason as important. The bars below the axis show the shares citing a reason as an important reason for easing. The dark portion of bars shows the share of banks citing a reason as "very important". Data covers the period from 1995 to 2025 where available, with a shorter time horizon for some questions that were added to the survey later.
**Source:** SLOOS.

To examine the interrelation between why and how banks change lending policies. We estimate regressions of the form:

$$\mathrm{y}_{b,t} = \alpha^{\mathrm{T,y}} + \sum_{r \in R} \beta_r^{\mathrm{T,y}} X_{r,b,t}^T$$

where $r$ indexes the potential reasons for changing lending lending policies, $X_{r,b,t}^T$ is an indicator for whether a bank $b$ cites $r$ as an important reason to tighten in $t$, and y is Price index$_{b,t}$ or Nonprice index$_{b,t}$. Banks only report reasons for tightening (easing) when they tighten (ease) at least one term, so $\beta_r^{\mathrm{T,y}}$ estimates how much reason $r$ being important affects a bank's tendency to tighten price or nonprice terms, conditional on tightening at least one term. We also run equivalent regressions predicting the supply changes by reported reasons for easing lending policies (with coefficients noted by an "E" superscript).

To ease interpretation, we group reasons into three buckets and aggregate the importance of a particular set of reasons for changing price or nonprice terms by those buckets. The buckets considered are: "Risk" reasons pertaining to the outlook, risk tolerance, and industry specific problems; "Competition" reasons pertaining to aggression of competition from other lenders, and "Capacity" reasons pertaining to secondary market liquidity or capital positions since those pertain to banks' ability to hold loans on balance sheet or move loans off the balance sheet.[5] To aggregate, note that the expected degree of tightening for variable y given a bank tightens at least one term is:

$$\mathbb{E}(\mathrm{y}|\text{Tightening something}) = \hat{\alpha}^{\mathrm{T,y}} + \sum_{r\in R} \hat{\beta}_r^{\mathrm{T,y}} \bar{X}_r^T,$$

where $\bar{X}_r$ is the share of banks that cite reason $r$ as an important reason to tighten (as shown in Figure 2). Equivalent expectations hold for easing. We aggregate by summing $\hat{\beta}_r^{\mathrm{T,y}} \bar{X}_r^T$ across $r$s within a particular grouping to shed light no how much that grouping contributes to changes in supply measures conditional on tightening or easing. A particular grouping is more important if either banks are more likely to cite that reason as important (a high $\bar{X}_r^T$) or a supply measure is highly sensitive to that particular reason (a high $\hat{\beta}_r^{\mathrm{T,y}}$).

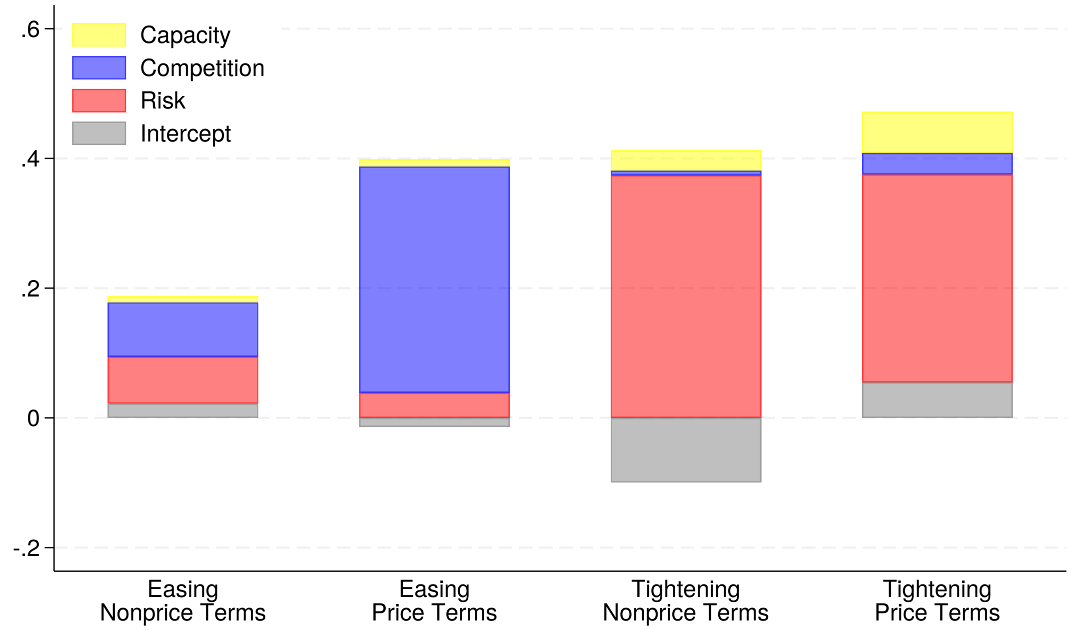
The outcomes of this decomposition are shown in Figure 3, while raw regression coefficients are reported in Figure A.2. The height of the bars pertain to the expected change in nonprice or price terms conditional on easing (first two columns) or tightening (last two columns) at least one term. Reported signs for easing are flipped so that higher values pertain to more easing. The height of the bars demonstrate that banks frequently tighten on both price and nonprice dimensions, whereas when they ease they are about twice as likely to ease price terms as non-price terms. Regarding reasons for the change, banks tend to *tighten* price and nonprice terms due to risk considerations. The most important factor here is concerns about the economic outlook which is both the most cited reason for tightening, and has the highest effect on the extent of tightening for both price and nonprice terms (i.e., the highest $\hat{\beta}_r^{\mathrm{T,y}}$ of the reasons for tightening). Meanwhile, banks tend to ease price terms due to competitive factors. This effect reflects competition being both the most common reported reason for easing, and the easing in price terms being particularly sensitive to whether banks cite competition as important: $\hat{\beta}_{\text{competition}}^{\text{E,price}}$ is at least three times larger than for any other reason for easing price or nonrprice terms. Finally, to the extent that banks ease nonprice terms, the change is due to a combination of risk and competition related reasons.

**Summary of self reported results** Overall, the analysis of loan terms in Section 2.2 demonstrates that lending standards and various terms tend to move together rather than get adjusted independently. The first principal component, basically measuring what share of terms banks report as tightening on net, accounts for about half of the variation in reported credit supply changes. The second dimension distinguishing credit supply changes generally reflects whether banks tighten on price or non-price terms.

Regarding why banks change supply, there is a stark asymmetry, with banks typically tightening credit supply due to changes in concern about loan performance and easing credit supply due to competitive pressures. This asymmetry in turn relates to how banks adjust supply. When banks tighten supply, they tend to tighten both price and non-price terms, and attribute the change to reasons related to credit risk. When banks ease supply, they tend to ease price terms, with

[5] We omit reasons related to liquidity positions and legislative, supervisory or accounting changes since those questions were added later and restrict thus including them restricts the sample.

Figure 3: **Reasons for Changing Price and Nonprice Terms**




**Notes:** This figure takes estimates from:

$$y_{b,t} = \alpha^{\mathrm{T,y}} + \sum_{r \in R} \beta_r^{\mathrm{T,y}} X_{r,b,t}^T$$

where $r$ indexes reasons, $X_{r,b,t}^T$ is an indicator for whether a bank cites $r$ as an important reason to tighten, and $y_{b,t}$ is Price index$_{b,t}$ or Nonprice index$_{b,t}$. Each bar segment plots $\sum_{r \in R_p} \hat{\beta}_r^{\mathrm{T,y}} \bar{X}_r^T$, for a particular partition $R_p$ of the reasons question: The Risk partition includes economic outlook, risk tolerance and industry specific problems; the Capacity partition includes capital position and secondary market liquidity; and Competition includes the aggression of competition from other lenders. The height of the bar estimates the supply response for an average bank (an $\bar{X}_r^T$ as in Figure 2) relative to one that reports no reasons in the partition as important. The sum of the bars, including the intercept in grey, gives the average change in the Price or Nonprice index conditional on tightening at least one term. Easing bars present equivalent estimates for banks that report easing at least one term, but with the sign reversed so that higher values mean more easing.
**Source:** SLOOS.

competitive factors predominantly driving the easing.

## 2.4 Using linked SLOOS-Call Report-Y-14 data to assess causes and implications of credit supply

### 2.4.1 Methodology

To investigate what motivates a bank to change credit supply or how such a change manifests in lending outcomes, we link SLOOS responses to banks' Call Report and Y-14 filings.[6] We then test how trends in banks' portfolios differ based on their reported changes in credit supply. Specifically,

[6]SLOOS respondents are banks rather than holding companies. When matching SLOOS responses to Y-14, we attribute the change in lending policies to the regulatory high holder.

we run regressions of the form:

$$y_{b,t+h} - y_{b,t-1} = \beta^h \text{Net Tightening index}_{b,t} + \Gamma^h \mathbf{X}_{b,t} + \tau_t^h + \epsilon_{b,t}^h \quad (1)$$

where $y_{b,t+h} - y_{b,t-1}$ is the change in a balance sheet characteristic of interest—loan rates, originations, performance, or balances—in the $h$ quarters since the SLOOS response. Net Tightening index$_{b,t}$ is the measure described in Section 2.2, reflecting the share of queried terms that banks reported tightening net of the share reported as having eased. $\mathrm{X}_{b,t}$ is a set of controls including Demand Index$_{b,t}$, measuring the bank's reported net change in C&I loan demand in the quarter (1 for stronger, 0 for unchanged, -1 for weaker), and one lag for the Net Tightening index and Demand index. $\tau_t^h$ is a quarter fixed effect. As the quarter fixed effects account for macroeconomic developments affecting demand and the demand control should capture more idiosyncratic developments affecting demand (such as growth prospects in a bank's markets), the estimate for $\beta^h$ should reasonably reflect the effects of changes in underwriting policies on lending over time. In some specifications, we replace the Net Tightening Index with measures that separate tightening from easing or net tightening in price and non-price terms.

The inclusion of the time fixed effect means that $\{\beta^h\}$ traces the expected movements in the outcome variable $y$ for banks that report tightening supply (on net) in quarter $t$ relative to banks that leave supply unchanged. $\beta$ reflects the estimated change in a given balance sheet item for a bank that tightens along all loan terms. The $t = 0$ response pertains to the quarter over which banks indicated they changed standards or terms in the SLOOS.

This approach allows us to be agnostic as to the timing with which various balance sheet developments relate to changes in standards. This flexibility is important due to the non-trivial dynamics involved. Supply decisions can both cause and be caused by certain balance sheet developments. For example, weak loan growth can cause banks to expand credit availability, supporting subsequent growth. Tracing out trends both before and after banks change supply is informative about the direction of causality.

### 2.4.2 How lending policies affect loan originations

We first use detailed contract-level data from the Y-14 to examine which terms actually move with the Net Tightening index and how is it reflected in loan originations. Figure 4 presents evidence that the fluctuations in the Net Tightening index resemble conventional changes associated with the reduction of credit supply of credit: higher prices and lower quantities. The top-left panel plots trends in the logarithm in the volume of new loan commitments, indexed to the quarter before the SLOOS response, while the top-right panel plots loan rate spreads for new originations.[7]

The figure shows that a net tightening in credit supply has the expected effects, causing a reduction in loan originations and an increase in loan rate spreads shortly after the change. Effects at time 0 are modest (an insignificant decline in originations and no change in spreads), but this

[7] Spreads are to LIBOR/SOFR for floating rate loans and maturity matched treasuries for fixed rate loans.

might be a timing issue. While banks report that lending conditions changed over quarter 0, we don't know when that change occurred. Consequently, we start seeing stronger effects in the quarter after the SLOOS response, when the shift in credit supply would be in effect for the full quarter. The estimates imply that a bank that tightened terms across the board would experience about 8 percentage point lower origination growth and increase loan rate spreads by about 8 basis points relative to the period before the survey response. The increase in spreads is more persistent, with spreads remaining elevated by about 10 basis points in quarters 2–5 before returning to normal in quarter 6. Origination volume, in contrast, remains depressed by about 8 percent in quarter 2, but normalizes by quarter 3.

While changes in lending volumes and prices are consistent with the expected effects of a supply contraction, the magnitudes suggest that the change is not a simple shift in a supply curve. The 8 percentage point drop in originations against an only 8 basis point increase in interest rates would imply an incredibly high demand elasticity. Instead these results suggest some change on the extensive margin causing origination volumes to decline for reasons beyond less-favorable loan pricing.

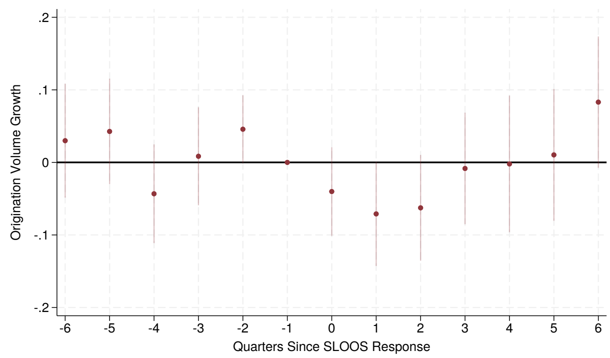
Are the effects of tightening and easing symmetric? The use of the Net Tightening index imposes symmetric effects of supply changes (e.g., tightening an additional term reduces credit as much as easing an additional one expands it). However, the analysis in Section 2.3 suggests that tightening might not be the simple reverse of easing. The bottom panels in Figure 4 include separate tightening and easing measures to accommodate potential asymmetries.

The figures show that, directionally, tightening and easing do indeed have opposite effects on origination volumes and pricing, but the magnitudes differ. Tightening reduces origination growth by about twice as much as easing increases it. In contrast, easing reduces loan rate spreads by about twice as much as tightening increases them. These patterns align with some of the previous results surrounding asymmetries between tightening and easing. Loan volumes being more sensitive to tightening than easing is consistent with tightening being more risk-motivated, as banks looking to reduce risk exposure are more likely to reduce credit on the extensive margin. Likewise, rates being more sensitive to easing is consistent with competition-motivated decisions, as lower rates may be needed to compete with other lenders.

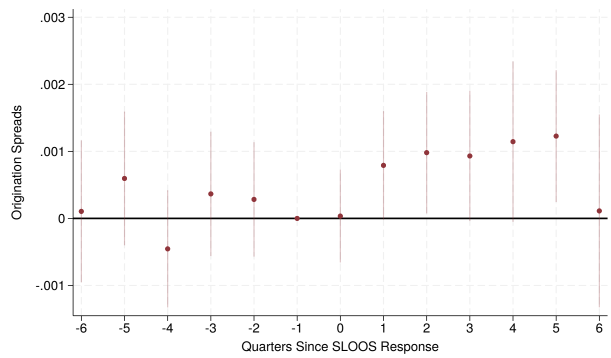
How does the composition of originations change? Given some of the non-price terms included in the Net Tightening index, one might expect that origination activity changes beyond simple changes in volumes or pricing (e.g., changes in collateralization, size, maturity, or borrower risk ratings). Likewise, the large drop in origination volumes suggests a potential decline in approvals that could change the compostion of borrowers.

Figure 5 presents estimates of $\beta^1$ from equation (1) for several variables pertaining to average characteristics of a bank's C&I loan originations: the share of new commitments that (i) have full or partial guarantees from a guarantor, (ii) are not classified as leveraged loans, (iii) have an investment grade internal risk rating (BBB or better), (iv) have a loan term under 3 years, (v) are secured by a first lien on collateral, and (vi) are to a relationship borrower (a borrower for which

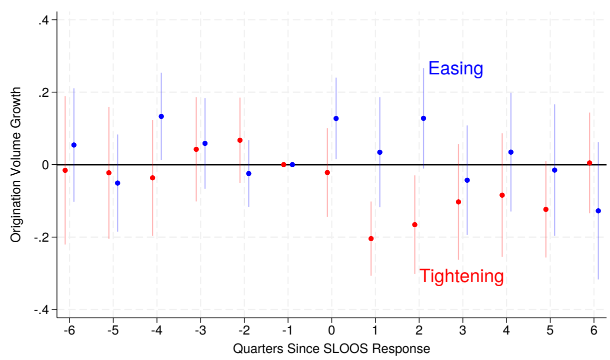
Figure 4: **Trends in Originations and Rates Around Tightening**



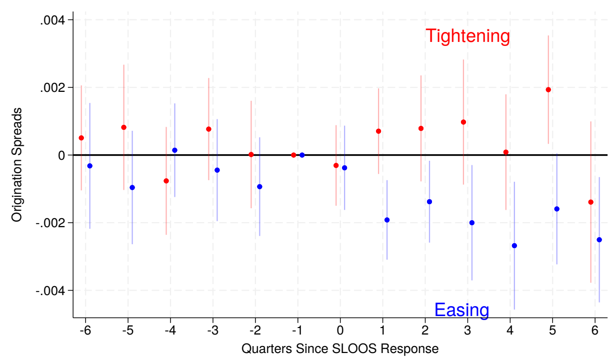

(a) C&I Origination Growth




(b) C&I Loan Rate Spreads




(c) C&I Origination Growth




(d) C&I Loan Rate Spreads

**Notes:** This figure plots the regression coefficients $\beta^h$ from (1) by time horizon $h$. Each figure plots estimates and 90% confidence intervals for $\{\beta^h\}$, where $y$ is the the natural logarithm of quarterly new C&I loan commitments (left) or the commitment-weighted average interest rate spread on new originations (right). The bottom panel presents results replacing the Net Tightening Index with a Tightening Index and Easing Index, separately measuring the share of terms a bank reported as tightening and easing, respectively. The sample covers the period from 2012 to 2025.
**Sources:** Y-14Q, SLOOS.

there is a record of previous borrowing in the Y-14). Each of these variables are constructed so that higher shares would generally be considered reflective of tighter credit. The estimates of $\beta^1$ for each variable thus measure the extent to which banks that reported tightening terms in the previous quarter actually tightened credit along the particular non-price dimension (relative to the quarter before reporting). We report the $t = 1$ effect since the change in pricing and origination volumes appeared with a one quarter lag.

Overall, reported changes in terms do not strongly relate to any of the studied terms/borrower characteristics. Nothing is significant at even the 10% level, and point estimates are modest. The largest predicted effect is that a bank that reports tightening along all queried dimensions (Net Tightening index= 1) reduces the share of originations that are considered leveraged loans by about 2 percent. The other effect sizes range from -1 percent to 1 percent and are far from statistically significant.

Figure A.3 presents equivalent estimates but separately estimating the effects of tightening and easing (left chart) or separately estimating the effects of tightening price and non-price terms (right chart). There is still limited evidence of changes in non-price terms or borrower composition. The only effects that are statistically significant at the 10% level are declines in leveraged lending for banks that tighten non-price terms on net or banks that tighten terms (i.e., the coefficient estimates on Non-price index and Tightening index, respectively).

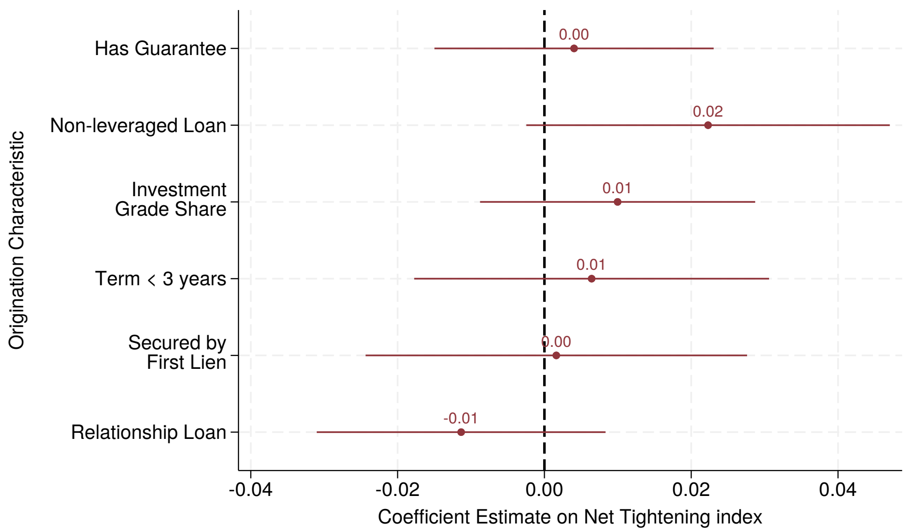
The lack of a change in non-price terms or the composition of borrowers may be somewhat surprising given that changes in credit supply are often motivated by risk management considerations. However, it is possible that banks are predominantly adjusting lending policies along difficult to observe dimensions. Some changes in risk characteristics, such as covenant stringency, are unobservable or difficult to measure. Likewise, even if banks do not make more loans with guarantees or first lien collateral, there can be subtler changes in the strength of guarantees (e.g., stronger guarantors) or collateralization (e.g., lower LTVs). Finally, if tighter credit takes the form of greater screening effort, this change would presumably make loans safer along dimensions that are unobservable to the econometrician rather than changes in readily observable risk metrics.

### 2.4.3 Portfolio-level dynamics

We now turn our attention to portfolio-level developments surrounding changes in lending policies. This work uses information from the Call Reports and thus covers a larger sample of banks and longer time period than analysis of the Y-14 data. Due to the longer available time series, we expand the time horizon to cover the two years before the change in lending policies out to five years after the change.

To preview the results, we find that in the quarters after banks report a net tightening in C&I policies, they tend to experience slower C&I loan growth and worse loan performance. When we analyze asymmetries in the effects of tightening and easing, we find patterns consistent with those in Figure 2. Namely, tighter policies are strongly associated with performance deterioration (consistent with tightening being driven by credit risk considerations) and easing in lending policies

Figure 5: **Changes in non-Price Terms**




**Notes:** This presents $\beta$ estimates from:

$$y_{b,t+1} - y_{b,t-1} = \beta \text{Net Tightening Index}_{b,t} + \Gamma \mathbf{X}_{b,t} + \tau_t + \epsilon_{b,t}$$

where $y$ is the share of loan originations that (i) have full or partial guarantees from a guarantor, (ii) are not classified as leveraged loans, (iii) have an investment grade internal risk rating (BBB or better), (iv) have a loan term under 3 years, (v) are secured by a first lien on collateral, and (vi) are to a borrower for which there is a record of previous borrowing in the Y-14. Red dots and lines present point estimates and 90% confidence intervals for $\beta$ for a particular loan term. Standard errors are clustered by quarter.
**Sources:** SLOOS, Y-14.

are precipitated by weak loan growth (consistent with elevated competitive pressures).

**Effects of Net Tightening** Figure 6 plots regression estimates for trends in the following variables around a change in C&I lending policies: C&I loan balances (top-left), total loan balances (top-right), non-performing loan rates (bottom-left) and cumulative net charge offs since time $t = 0$ (bottom-right).

Panel (a) plots merger-adjust C&I loan growth since the quarter before the survey response. C&I loan balances start to fall after banks tighten policies on net. A bank that tightens all queried terms is estimated to have loan growth that is roughly 4 percentage points lower after a year, and nearly 10 percentage points lower after 5 years, each relative to a bank that reports not changing their lending terms.

Panel (b) plots equivalent estimates for overall loan growth. Thought the measure of net tightening in loan terms is C&I specific, Figure 2 demonstrates that many of the common underlying reasons for changing C&I lending policies are not necessarily C&I specific (e.g., changes in concern about the economic outlook or risk tolerance). Consequently, banks that tighten policies might see other types of loans decline as well. We indeed see that overall loan growth declines after banks tighten C&I policies, albeit by only about half as much as for C&I loans: a unit increase in the Net Tightening index reduces total loans balances by about 2 percentage points after 1 year and 5 percentage points after 5 years.

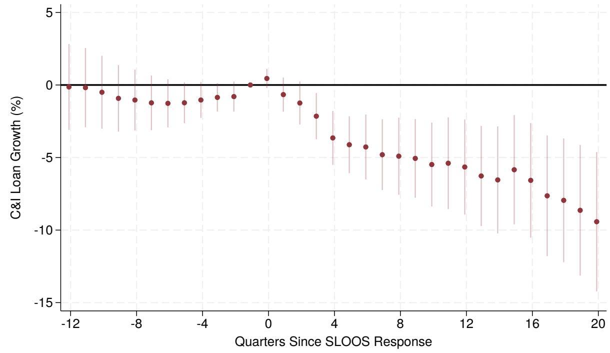
Panels (c) and (d) show that C&I nonperforming loan and net charge-off rates, respectively, both rise following a tightening in C&I lending policies. A unit increase in the Net Tightening index is associated with a roughly 25 basis point increase in non-performing loan rates in the year after the survey response. The nonperforming loan rate then remains persistently elevated, suggesting that resolutions of troubled loans are offset by continued instances of default. This deteriorating loan performance prompts a steady rise in cumulative charge-offs in the years following tightening, reaching about 28 basis points (as a share of the C&I loan portfolio) after 3 years.

Additionally, Figure A.4 demonstrates the merit of accounting for the range of terms that banks report adjusting. Each panel presents equivalent analysis, but adding additional controls for the reported net tightening in lending standards—the measure of credit supply emphasized in most of the previous literature using SLOOS to measure credit supply fluctuations. Tighter lending standards are not associated with weaker credit flows when the broader Net Tightening index is included in the specification.

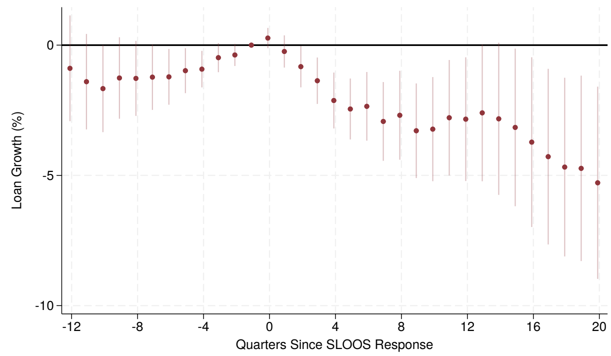
**Asymmetric effects** Finally, we investigate whether there are asymmetric effects of tightening and easing. Figure 7 presents estimates breaking the Net Tightening index into the Tightening and Easing indexes.

The main take away is that patterns in loan growth and loan performance are consistent with mechanisms implied by the asymmetric reasons for tightening and easing (i.e., easing being driven by competitive factors and tightening by risk considerations). First, we see a decline in C&I loan balances in the couple of years before banks report easing C&I lending policies but no increase before

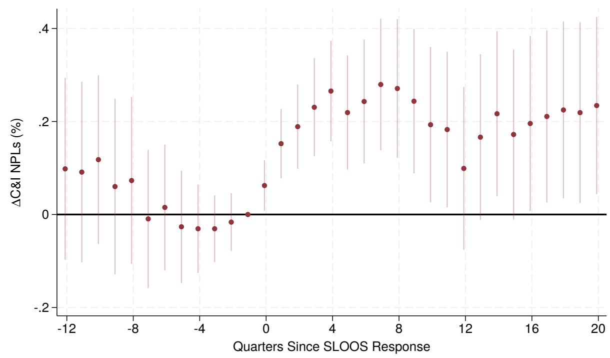
Figure 6: **Trends in Portfolios Around a Change in Supply**



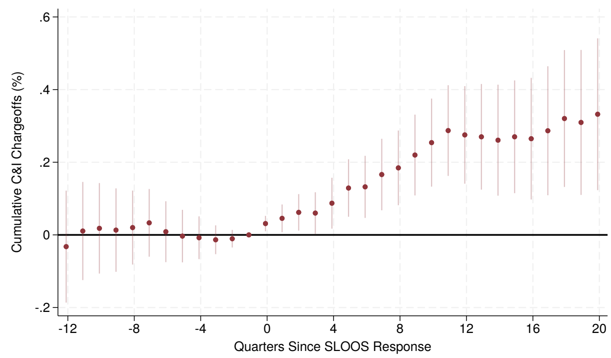

(a) Change in C&I loan balances




(b) Change in Total loan balances




(c) Change in C&I Nonperforming Loan Rate




(d) Cumulative C&I Net Charge-offs

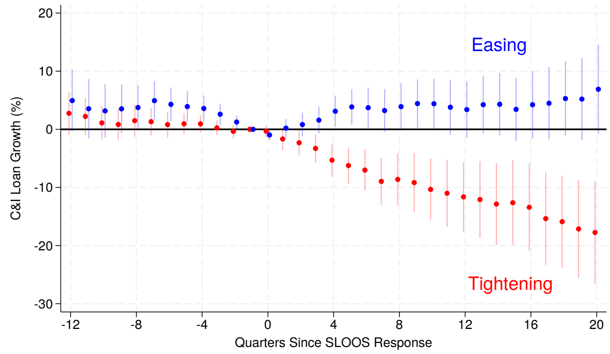
**Notes:** This figure plots the regression coefficients from (1) by time horizon $h$. Each figure plots estimates and 90% confidence intervals for $\{\beta^h\}$, where $y$ is ln(C&I Loan Balances) in a, ln(Total Loan Balances) in b, the C&I loan nonperforming loan rate in c, and cumulative C&I loan charge-offs in d. The sample covers the period from 1990 to 2025.
**Sources:** Call Reports, SLOOS.

tightening (top-left panel). This outcome is consistent with banks easing policies to stem balance declines due to competition from other lenders. C&I loan balances increase after easing, indicating that the change in policies indeed supports loan growth. Additionally, the fact that loan balances more broadly do not increase when banks ease policies is consistent with easing reflecting factors specific to the C&I market (i.e., loan competition) rather than cross-loan-category developments such as changes in the economic outlook or risk tolerance (top-right panel).

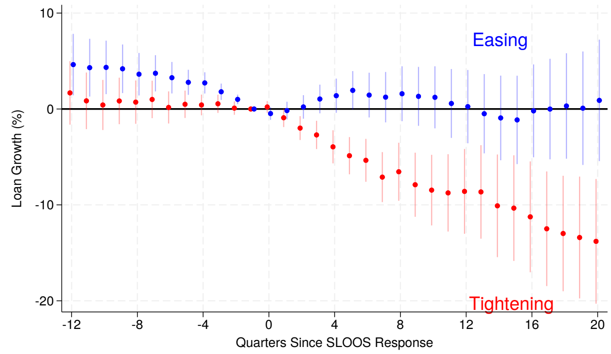
Second, tightening is more strongly associated with changes in loan performance than easing. Banks that tighten policies observe a sizeable increase in nonperforming loan rates shortly after tightening (bottom-left panel), and steady rise in cumulative charge-offs over the following years (bottom-right panel). In contrast, changes in loan performance following an easing of lending policies are smaller, typically statistically insignificant, and inconsistent across performance measures (nonperforming loan rates rise but charge-offs fall).

Third, loan balances respond more to tightening than easing. A given tightening in policies

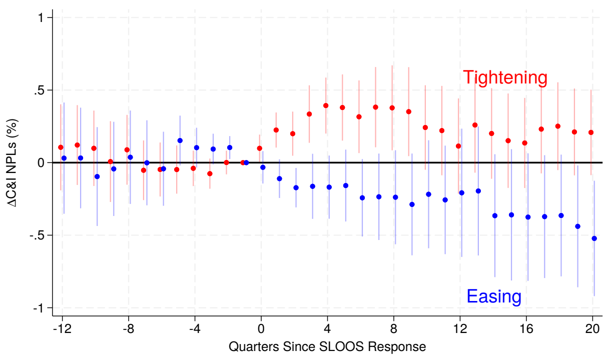
Figure 7: **Trends in Portfolios Around a Change in Supply, Asymmetry in Tightening and Easing**



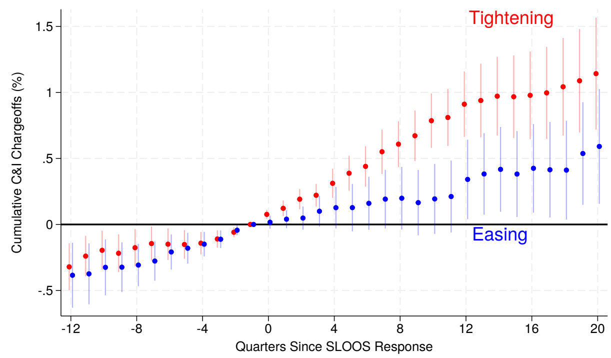

(a) Change in C&I loan balances




(b) Change in Total loan balances




(c) Change in C&I Nonperforming Loan Rate




(d) Cumulative C&I Net Charge-offs

**Notes:** This figure plots the regression coefficients from (1) by time horizon $h$, but with Tightening Index and Easing Index entering separately instead of as the Net Tightening index. Each figure plots estimates and 90% confidence intervals for the coefficient on Tightening index (red) and Easing index (blue), where $y$ is ln(C&I Loan Balances) in a, ln(Total Loan Balances) in b, the C&I loan nonperforming loan rate in c, and cumulative C&I loan charge-offs in d. The sample covers the period from 1990 to 2025.
**Sources:** Call Reports, SLOOS.

reduces C&I loan balances after tightening by roughly twice as much as easing increases balances. This difference may reflect a combination of tightening entailing more of a change in the extensive margin (i.e., fewer approvals) and the fact that banks that ease are facing greater competitive pressures that might have resulting in lower C&I balances independent of changes in policies.[8]

[8]Regarding the first effect, tightening is more correlated with the Non-price index than the Price index, whereas easing bears a stronger correlation with the Price index. Since the non-Price index includes changes in standards for loan approvals, this might cause tightening to pick up more extensive margin changes. Indeed Figure A.5 shows that the decline in C&I loan balances after tightening is more pronounced when it is non-price terms that are tightened, though the difference goes away at longer time horizons.

### 2.5 Summary of empirical results and implications for quantitative model

This section summarizes the empirical results and describes how these results inform the structure of the model we introduce in Section 3. We organize this summary around three questions: (i) *why* do banks change lending standards? (ii) *what do banks do* when they change lending standards? and (iii) *what happens after* banks change their lending standards?

#### 2.5.1 Why do banks change standards?

Figure 2 reveals a stark asymmetry in banks' self-reported motivations for adjusting lending standards. When *tightening*, banks primarily cite risk factors (e.g. deteriorating economic outlook, reduced risk tolerance, industry-specific problems); by contrast, when *easing*, they primarily cite competitive pressures (e.g. increased competition from other lenders). These survey responses are borne out in the "hard" data on bank financial statements and portfolio construction. For example, Figure 6 shows that banks experience rising nonperforming loan and charge-off rates after tightening lending policies, consistent with the realization of elevated credit risks, while banks that ease policies experience weak loan growth beforehand, consistent with competitive pressures.

**Model implications** We capture these asymmetric forces in our model by setting up two distinct—but potentially related—channels. On the risk side, banks are uncertain about the quality of the loan applicant pool they face; Rather than observing pool quality directly, they learn about it over time, making inference based on realized loan returns given their loan policies. Tighter lending policies can reflect negative signals about credit quality that materialize as weaker loan performance even though the effect of the tighter policies themselves is to improve the quality of new loans. Though the empirical work focuses on the cross-section, the model is designed to study the dynamics associated with both idiosyncratic and aggregate shocks to pool quality.

On the competition side, banks compete monopolistically, choosing loan rates given demand curves that depend on terms set by other banks and a non-bank financial sector. Banks may experience both idiosyncratic and aggregate demand shocks: the former reshuffles loan demand *within* the banking sector, while the latter—say from a price reduction by the non-bank sector—reallocates demand *across* financial sectors.

#### 2.5.2 How do banks implement changes in standards?

The empirical results indicate that the two key dimensions when characterizing changes in lending policies are whether banks are changing price or non-price terms (Figure 1). These methods of adjusting supply also relate to the primary motivations for changing supply; competitive pressures tend to motivate easing in price terms, while concerns related to loan performance tend to affect both price and non-price terms. This asymmetry appears in both banks self-reported changes in lending policies (see Figure 3) and in the hard data (see Section 2.4).

Two additional patterns suggest that screening may be central to changes in non-price terms. First, reported changes in lending policies have low correlation with changes in contractual terms (maturity, collateral), highlighting the role of the extensive approval margin over intensive adjustment of contractual features. Second, changes in lending policies relate weakly to borrower credit ratings, suggesting that banks may be working harder to identify risky borrowers rather than change their willingness to lend to known risky borrowers.

**Model implications** Both price and non-price terms are important modes of adjustment. Our model parsimoniously captures these separate channels by allowing banks to make two separate loan-side policy choices: loan rates (price) and approval rates (non-price). We implement a meaningful approval margin using an intensive screening margin, which implies that banks can cut loan supply by investing in weeding out more bad borrowers rather than raising rates across all borrowers. We focus on screening as the relevant non-price term based on the observations that reported changes in lending policies (i) affect loan volumes more than pricing, and (ii) relate weakly to origination terms and borrower credit ratings.[9]

As explored below, this dynamic separates our work from much of the existing literature on how banks respond to economic shocks. This allows our model to match the empirical observation that upon tightening, loan volumes change without meaningful changes in loan rates more. Importantly, we design the model so that risk concerns lead banks to adjust both margins, raising rates and increasing screening intensity, with screening effects being quantitatively larger. Competition concerns, in contrast, operate predominantly through pricing, with banks lowering rates to maintain market share while keeping screening standards. This reflects the empirical pattern that tightening affects both dimensions while easing operates predominantly through pricing.

### 2.5.3 What happens after banks change standards?

A sharp implication of Figure 4 is that volume effects far exceed price effects when banks tighten: loan originations decline by approximately 1 *percentage* point per 1 *basis* point increase in loan rates. When banks ease, this effect primarily shows up as a reduction in loan rates at origination. Another important feature of the data is that banks still observe increases in charge-off rates well after tightening standards. This suggests that while banks can *identify* and *respond to* an increase in portfolio risk, they generically cannot *eliminate* its adverse effects. This suggests either imperfect learning, imperfect screening, or the simple fact that certain loan outcomes take considerable time after origination to materialize. Notably, non-performing loan rates increase and then return to normal more quickly, further suggesting that banks can intervene more successfully on new originations.

[9] Specifically, the decline in loan volumes suggests a change in approvals that causes loan volumes to fall independent of pricing. The lack of a response in origination characteristics observable to the econometrician suggests that the decline in volumes reflects banks increasing their identification of weak borrowers rather than decreasing their willingness to lend to such borrowers (and causing a shift to observably safer loans).

**Model implications** The model features described to this point allow for the *possibility* of these outcomes, but do not impose them. This implies that the ability to endogenously generate these asymmetric patterns can provide key quantitative discipline on the model. This is discussed in more detail in Section 4, when we map the model to the data and validate its quantitative performance.

# 3 A Quantitative Model of Lending Standards

This section develops a model with financially constrained, heterogeneous banks capable of confronting the above observations about credit supply dynamics. The data require that the model must deliver two novel features. First, it must disentangle lending standards from loan quantities and prices. To this end, we introduce a screening or loan approval decision for banks. Second, the model must capture the asymmetric response of standards to risk and competitive factors: banks should tighten in response to deteriorating loan performance and ease in response to competitive pressures. For the former, we introduce learning into the banks' screening decisions: banks adjust their priors about how effectively they screen out bad borrowers in response to realized portfolio-wide loan returns. For the latter, we allow for competition both between banks within the banking sector and between banks and non-bank lenders.

## 3.1 Environment

**Basics** We consider a stationary economy populated by a unit mass of monopolistically competitive banks, a unit mass of competitive non-banks, and a unit mass of entrepreneurs.[10] Since entrepreneurs demand loans from both banks and non-banks, we use the terms "entrepreneur" and "borrower" interchangeably in what follows. Since the model is designed to understand credit supply dynamics, we treat the entrepreneurs and non-banks as effectively static in their decisions. Time is discrete and infinite, and there is a single good. The (exogenous) risk-free rate is $r_f$.

**Entrepreneurs** There are two types of entrepreneurs. Good entrepreneurs (population share $\mu_\rho$) operate a decreasing returns to scale technology which takes capital $k$ and labor $n$ as inputs. Output is $f(k,n) = k^\gamma n^\eta$ with $\gamma + \eta < 1$, and profits net out factor costs $g(k,n) = \overline{r}k + \overline{w}n$ given the exogenously specified rental rate on capital $\overline{r}$ and wage rate $\overline{w}$. Entrepreneurs have no internal funds and operate their technology subject to a working capital constraint: they must finance a fraction $\kappa$ of their total input costs $g(k,n)$ with loans.

Bad entrepreneurs (population share $1 - \mu_\rho$) operate no technology and simply abscond with a fraction $\lambda$ of the funds lent to them. Therefore, no lender will lend to an entrepreneur identified as the bad type. Since the stolen principal represents a private benefit to bad types, though, they still optimally demand loans. The only equilibrium in which bad types can obtain credit, then, is

[10] We focus on a stationary model since our empirics use quarter fixed effects and so highlight cross-sectional variation. The set-up is similar to that in **?**.

a pooling equilibrium. Therefore, critically, bad borrowers will mimic good borrowers in their loan demand: any other behavior would reveal them as bad types and lead to rejection.

**Loan demand** Individual borrowers' total debt $L$ is a constant elasticity of substitution (CES) aggregate of borrowing from the bank and non-bank sectors, $L_b$ and $L_n$, which are in turn CES aggregates of borrowing from individual banks and non-banks, $L_{ij}$ for sector $i$ and insititution $j$:

$$L = \left[ \sum_i \zeta_i^{\frac{1}{\varepsilon}} L_i^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \quad \text{where} \quad L_i = \left[ \int_0^1 \omega_{ij}^{\frac{1}{\phi_i}} L_{ij}^{\frac{\phi_i-1}{\phi_i}} \mathrm{d}j \right]^{\frac{\phi_i}{\phi_i-1}} \quad \text{for } i \in \{n, b\} \tag{2}$$

The parameters $\varepsilon$ and $\phi_i$ govern the elasticity of substitution between sectors and specific institutions, respectively. The parameters $\zeta_i$ measures the intensity of sector $i$ in the demand for total loan services. Since we assume that all non-banks behave symmetrically and competitively, we do not explicitly model the non-bank sector other than to assume that they lend at composite interest rate $r_n = r_f + \iota_n$, where $\iota_n$ represents the sectoral spread over the risk-free rate. That is, we do not directly specify $\phi_n$ or $\{\omega_{nj}\}$. To conserve notation, we define $\phi_b = \phi$ and $\{\omega_{bj}\} = \{\omega_j\}$. We assume that the bank-level demand shifter $\omega$ follows an AR(1) process summarized by $G_\omega(\omega'; \omega)$.

**Applicant pool quality** The applicant pool at each bank is a random sample from the population: the share of good types applying to each bank is $\rho$. Overall quality $\rho = \rho_f + \rho_n$ is the sum of a fundamental component, $\rho_f$, and a noise component, $\rho_n$. We assume that while banks can infer $\rho$ by observing approval rates and loan returns (described below), they cannot separate the two components. The fundamental component is drawn from a distribution $G_{\rho_f}(\rho_f; \mu_{\rho_f}, \sigma_{\rho_f}) = \mathcal{N}(\mu_{\rho_f}, \sigma_{\rho_f})$, where $\mathcal{N}$ denotes the normal distribution, and likewise the noise component follows $G_{\rho_n}(\rho_n; \mu_{\rho_n}, \sigma_{\rho_n}) = \mathcal{N}(\mu_{\rho_n}, \sigma_{\rho_n})$. We assume that $\mu_{\rho_f} = \mu_\rho$ and that $\mu_{\rho_n} = 0$ to ensure that the economy-wide applicant pool (integrating across all banks) still has mean $\mu_\rho$. The overall dispersion in applicant pool quality across banks is measured by $\sigma_\rho^2 = \sigma_{\rho_f}^2 + \sigma_{\rho_n}^2$. Each period, a bank draws a new fundamental component with i.i.d. probability $\pi_{\rho_f}$: when this shock hits, a bank knows *that* it has drawn a new $\rho_f$, but not *what* the new $\rho_f$ is.

**Screening technology** We assume that the bank correctly identifies all good types, but correctly identifies and screens out only a fraction $\delta(s)$ of bad types, where $s$ is the bank's chosen screening intensity. Screening incurs a per-application cost $c(s)$, which is increasing, convex, and satisfies $c(0) = 0$. The function $\delta(s)$ is strictly increasing (and therefore invertible), concave, and satisfies $\delta(0) = 0$.[11] For a given mass of applicants, then, the share of applications approved by a bank with applicant pool quality $\rho$ that screens at intensity $s$ is

$$\alpha(\rho; s) = \rho + (1 - \rho)(1 - \delta(s)) \tag{3}$$

[11] If it does not screen, the bank incurs no costs, but does not weed out any bad applicants.

A higher-quality applicant pool raises the approval rate for any screening level, while increased screening lowers the approval rate for a given applicant pool. Therefore increases in both pool quality and screening increase the share of good borrowers in the pool of approved loans,

$$\tilde{\rho}(\rho; s) = \frac{\rho}{\alpha(\rho; s)} \tag{4}$$

**Loans, returns, and inference** These technologies imply that the lending policy $(r, s)$ fully determines both its total loan volume $\ell'$ and its per unit loan return $r'$ conditional on $\rho$:

$$\ell' = \mathcal{L}(\rho; r, s, \omega) = \alpha(\rho; s) L(r; \omega) \tag{5}$$

$$r' = \mathcal{R}(\rho; r, s) = r\tilde{\rho}(\rho; s) - \lambda(1 - \tilde{\rho}(\rho; s)) \tag{6}$$

Equation (5) defines the quantity of funded loans as the product of the amount $L$ lent to each approved loan and the share $\alpha$ of the total borrowers the bank faces. Equation (6) reflects the fact that if the bank charges loan rate $r$, it will earn $1 + r$ on all loans to good borrowers (share $\tilde{\rho}$), and $1 - \lambda$ on all loans to bad borrowers (share $1 - \tilde{\rho}$). Since $\rho$ is unknown at the time at which the rate and screening policies are chosen, the realizations of both $\ell'$ and $r'$ are uncertain ex ante.

After observing either $\ell'$ or $r'$, then, a bank can use either (5) or (6) to infer the share of good types to whom it lent last period, $\rho$. Given the timing of the model, we present inference as based on $\ell'$. Since our assumptions on $\delta$ imply that $\alpha$ is invertible in $\rho$ conditional on $s$, the bank can infer the pool quality it faced in the current period according to:

$$\rho(\ell'; r, s, \omega) = 1 - \frac{1 - \frac{\ell'}{L(r;\omega)}}{\delta(s)} \tag{7}$$

where the right-hand side represents the inverse of $\alpha(\cdot)$ for a fixed $s$. Since equation (7) defines a one-to-one mapping between $\ell'$ and $\rho$, we may analyze the uncertainty a bank faces with respect to either: in what follows, we choose $\rho$, consistent with the banks' information sets.

**Learning** A key friction in the model is that a bank directly observes only the composite $\rho$, rather than $\rho_f$ and $\rho_n$ separately. In this environment, then, a bank infers its fundamental $\rho_f$ as best it can in order to correctly assess its applicant pool quality. Suppose that a bank has inferred a sequence $\mathcal{P} = \{\rho_t\}_{t=1}^{h}$ of realizations of $\rho$ of length $h$ with sample mean $\overline{\rho} = h^{-1} \sum_{t=1}^{h} \rho_t$ since it last drew a new $\rho_f$. Given our distributional assumptions, $\overline{\rho}$ and $h$ are sufficient statistics for what a bank needs to know about $\mathcal{P}$ to assess its applicant pool.[12] As a result, a bank's posterior beliefs about its $\rho_f$ can be represented by the normal distribution $\mathcal{N}\left(\hat{\mu}_{\rho_f}(\overline{\rho}, h), \hat{\sigma}_{\rho_f}(h)\right)$, where

$$\hat{\mu}_{\rho_f}(\overline{\rho}, h) = \frac{h\sigma_{\rho_f}^2 \overline{\rho} + \sigma_{\rho_n}^2 \mu_{\rho_f}}{h\sigma_{\rho_f}^2 + \sigma_{\rho_n}^2} \quad \text{and} \quad \hat{\sigma}_{\rho_f}(h)^2 = \frac{\sigma_{\rho_f}^2 \sigma_{\rho_n}^2}{h\sigma_{\rho_f}^2 + \sigma_{\rho_n}^2} \tag{8}$$

[12] This formulation adapts a similar structure in the context of heterogeneous firms from Senga (2022).

Since banks infer $\rho$ by (7) and do not observe $\rho_f$ and $\rho_n$ separately, it is useful to define the posterior distribution of $\rho$. Since $\rho_f$ and $\rho_n$ are independent and normally distributed and $\mu_{\rho_n} = 0$, then, the bank perceives that $\rho \sim F_\rho(\rho; \overline{\rho}, h) = \mathcal{N}\left(\hat{\mu}_\rho(\overline{\rho}, h), \hat{\sigma}_\rho(h)\right)$ where

$$\hat{\mu}_\rho(\overline{\rho}, h) = \hat{\mu}_{\rho_f}(\overline{\rho}, h) \quad \text{and} \quad \hat{\sigma}_\rho(h)^2 = \hat{\sigma}_{\rho_f}(h)^2 + \sigma_{\rho_n}^2 \tag{9}$$

Upon observing that $\rho_f$ has been re-drawn, the bank has no observations to use to update its beliefs: therefore, its beliefs coincide with the primitive distribution, i.e. $\hat{\mu}_\rho(\overline{\rho}, 0) = \mu_\rho$ and $\hat{\sigma}_\rho(0) = \sigma_\rho$. As $h \to \infty$, $\overline{\rho} \to \rho_f$ (which implies that $\hat{\mu}_\rho \to \rho_f$) and $\hat{\sigma}_{\rho_f}(h) \to 0$ (which implies that $\hat{\sigma}_\rho \to \sigma_{\rho_n}$).

**Bank financing and constraints** Each bank uses its net worth or internal financial capital $n$, newly issued equity $e < 0$, and deposits $d' \geq 0$ to make loans. Deposits are risk-free (insured) and issued at exogenous rate $r_d$ for all banks. We assume $r_d < r_f$, reflecting a liquidity premium on deposits. Banks value dividends $e \geq 0$ and face costs of issuing equity: we follow the dynamic corporate finance literature and model banks' preferences for dividends via the increasing function $\psi(e)$. The value of positive dividends is simply $\psi(e) = e$, but equity issuance is costly: that is, $\psi'(e) > 1$ for $e < 0$. Banks face a regulatory capital constraint that specifies that total lending, scaled by a factor $\chi$, may not exceed the total value of equity, reflecting the current period's lending and financing decisions. Finally, we assume that each bank exits with exogenous probability $\pi_e$ at the beginning of the period. In the event of an exit, the bank pays out its net worth as a dividend.

**Timing** The timing of the model within a period is as follows:

1. Banks realize returns $r'$ on loans made in the previous period.
2. Bank exit shocks are realized. Exiters are replaced with new banks with $n = n_e$, a draw of $\rho_f$ from $G_{\rho_f}$, and a draw of $\omega$ from $\overline{G}_\omega$, the ergodic distribution of $G_\omega$.
3. Active banks learn whether they have drawn a new $\rho_f$.
4. Banks learn their new demand shifter shocks $\omega$.
5. Banks choose a lending policy $(r, s)$.
6. Banks realize $\ell'$ and infer their current $\rho$, using this to update their beliefs $F_\rho$.
7. Banks choose a financing policy $(d', e)$.

## 3.2 Equilibrium

### 3.2.1 Entrepreneurs' problem

Given the fact the bad types must mimic the good types, we can derive entrepreneurial loan demand by considering the problem of the good entrepreneurs. Taking the set of loan rates $\{r_j\}$ across all banks $j \in \{0,1\}$ and the non-bank loan rate $r_n$ as given, the entrepreneur chooses total loan demand and factors of production according to

$$\max_{k,n,L} f(k,n) - g(k,n) + L - \frac{1+\tilde{r}}{1+r_f} L \text{ subject to: } L \geq \kappa g(k,n) \tag{10}$$

The entrepreneur's objective function in (10) trades off static profits from production today against required loan repayments tomorrow subject to the working capital constraint. The loan rate index $\tilde{r}$ is a CES aggregate of the sector-specific rate indices $r_n$ and $r_b$, defined below.

At the same time, the entrepreneur sources a given quantity of total loans $L$ at the lowest possible cost, solving the set of nested cost minimization problems given the aggregators in (2):

$$\min_{\{L_i\}} \sum_i (1+r_i) L_i \quad \text{subject to} \quad \left[\sum_i \zeta_i^{\frac{1}{\varepsilon}} L_i^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}} \geq L \tag{11}$$

$$\min_{\{L_{ij}\}} \int_0^1 (1+r_{ij}) L_{ij} \mathrm{d}j \quad \text{subject to} \quad \left[\int_0^1 \omega_{ij}^{\frac{1}{\phi}} L_{ij}^{\frac{\phi-1}{\phi}} \mathrm{d}j\right]^{\frac{\phi}{\phi-1}} \geq L_i \tag{12}$$

Our functional form assumptions for $f$ and $g$ yield the following closed-form demand system:

$$L(r_L) = \kappa(\gamma+\eta) \left[\frac{\left(\frac{\gamma}{\bar{r}}\right)^{\gamma} \left(\frac{\eta}{w}\right)^{\eta}}{1+\kappa\left(\frac{1+r_L}{1+r_f}\right)}\right]^{\frac{1}{1-\alpha-\eta}} \tag{13}$$

$$L_i(r_i; r_L) = \zeta_i \left(\frac{1+r_i}{1+\tilde{r}}\right)^{-\varepsilon} L(r_L) \tag{14}$$

$$L_{ij}(r_{ij}; r_i, r_L) = \omega_j \left(\frac{1+r_{ij}}{1+r_i}\right)^{-\phi} L_i(r_i; r_L) \tag{15}$$

where the aggregate and bank-sector-specific price indices are defined by standard CES aggregates:

$$1 + r_L = \left[\sum_i \zeta_i (1+r_i)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{16}$$

$$1 + r_i = \left[\int_0^1 \omega_{ij} (1+r_{ij})^{1-\phi} \mathrm{d}j\right]^{\frac{1}{1-\phi}} \tag{17}$$

Equations (13), (14), and (15) correspond to the aggregate, sector, and lender-specific loan demand, respectively. Equations (16) and (17) define the aggregate and sector interest rate indices which serve as the "benchmarks" in the CES demand functions above.

### 3.2.2 Banks' decision problem

**Exit and demand shocks** Let $V(n, \omega, \overline{\rho}, h)$ denote the value of a bank with net worth $n$, demand shifter $\omega$, and posterior beliefs summarized by $\overline{\rho}$ and $h$ at the lending phase. Let $W(n, \omega, \overline{\rho}, h)$ denote the value after loan return realizations and belief updating at the beginning of the period:

$$W(n,\omega,\overline{\rho},h) = (1-\pi_e)\psi(n) + \pi_e \int_\Omega \left[(1-\pi_{\rho_f})V(n,\omega',\overline{\rho},h) + \pi_{\rho_f} V(n,\omega',\mu_\rho,0)\right] \mathrm{d}G_\omega(\omega';\omega) \quad (18)$$

The first term in (18) reflects exit. A surviving bank that retains its $\rho_f$ enters the lending phase with its existing state; one that draws a new $\rho_f$ keeps its financial state, but re-adjusts its beliefs. In either case, the bank takes expectations over the realization of its demand shock, $\omega$.

**Lending phase** At the lending ($L$) phase, a bank solves:

$$\begin{aligned}
V_L(n,\omega,\overline{\rho},h) \quad &= \quad \max_{r,s} \int V_F\left(\ell', r' \;;\; n', \omega, \overline{\rho}', h+1\right) \mathrm{d}F_\rho(\rho;\overline{\rho},h) && (19)\\
\text{subject to: [demand]} \quad & \quad \ell' = \mathcal{L}(\rho;r,s,\omega) \text{ for all } \rho && (20)\\
\text{[returns]} \quad & \quad r' = \mathcal{R}(\rho;r,s) \text{ for all } \rho && (21)\\
\text{[net worth]} \quad & \quad n' = n - c(s)L(r;\omega) && (22)\\
\text{[belief updating]} \quad & \quad \overline{\rho}' = \frac{h\overline{\rho}+\rho}{h+1} \text{ for all } \rho && (23)
\end{aligned}$$

The objective function (19) reflects the bank's expected payoff across all possible realizations of $\rho$, weighted according to the bank's current beliefs about its screening ability. The value function at the financing phase, $J$, is conditional on the updates of the bank's states implied by its choices and realization of $\rho$. The lending policy $(r,s)$ pins down the actual loan volume and returns across all $\rho$, as described in constraints (20) and (21). Since the bank must finance screening costs per loan application, net worth at the financing stage is $n - c(s)L(r;\omega)$, defined in equation (22). Lastly, equation (23) is a recursive formulation of how the average of the sequence of $\rho$ realizations will be updated upon the next realization.

**Financing phase** After realizing $\rho$ (and $\ell'$ and $r'$), the bank must choose how to finance its loans:

$$\begin{aligned}
V_F(\ell', r' \;;\; n,\omega,\overline{\rho},h) \quad &= \quad \max_{d'\geq 0, e} \psi(e) + \frac{1}{1+r_f} W(n',\omega,\overline{\rho},h) && (24)\\
\text{subject to: [budget]} \quad & \quad \ell' + e \leq n + d' && (25)\\
\text{[capital requirement]} \quad & \quad \chi\ell' \leq \ell' - d' && (26)\\
\text{[net worth accum.]} \quad & \quad n' = (1+r')\ell' - (1+r_d)d' && (27)
\end{aligned}$$

The objective function (24) reflects the bank's current flow valuation of dividends and the discounted expected continuation value associated with its current choices. Note that there is no uncertainty in this phase (other than that already accounted for in $W$). The budget constraint (25) states that total lending plus any dividends paid out must come from the bank's internal capital or deposit issuance. Issuing equity ($e < 0$) eases the budget constraint. Equation (26) is the capital requirement. Equation (27) is the law of motion for the bank's net worth, which is comprised of the net profits from this period's lending and deposit financing.

### 3.2.3 Evolution of bank distribution

To conserve notation, we summarize the bank state at the lending phase by $x = (n, \omega, \overline{\rho}, h)$. We denote the optimal policy for choice variable $y$ in the bank problem by $g_y(x)$. Choices at the financing stage depend on the realization of $\rho$ in addition to the lending phase state $x$, and so we adopt the notation $g_y(\rho; x)$ for these policies.

Given a current distribution of banks over states $m(n, \omega, \overline{\rho}, h)$, the mass of banks next period with a particular state $(n', \omega', \overline{\rho}', h')$ is

$$\begin{aligned} m'(n', \omega', \overline{\rho}', h') \quad = \quad & \pi_e \Big[ \int_x G_\omega(\omega'; \omega(x)) \int_\rho \mathbf{1} \left[ n' = \hat{n}\left(\rho; g_r(x), g_s(x), g_{d'}(\rho; x)\right)\right] \\ & \quad \times \left( \pi_{\rho_f} \mathbf{1}\left[\overline{\rho} = \mu_\rho, h' = 0\right] + (1 - \pi_{\rho_f}) \mathbf{1}[\overline{\rho}' = \hat{\overline{\rho}}(\rho; \overline{\rho}(x), h(x)), h' = h(x) + 1] \right) \\ & \quad \times \mathrm{d}F_\rho(\rho; \overline{\rho}(x), h(x)) \mathrm{d}m(x) \Big] \\ & + (1 - \pi_e) \mathbf{1}\left[n' = n_e, \overline{\rho} = \mu_\rho, h' = 0\right] \overline{G}_\omega(\omega') \end{aligned} \tag{28}$$

where the function $\hat{n}(\rho; r, s, d')$ encodes the law of motion for net worth defined in equations (22) and (27) and the function $\hat{\overline{\rho}}(\rho; \overline{\rho}, h)$ encodes the law of motion for beliefs defined in equation (23). The two integrals reflect that we integrate over both the current distribution of banks over states and the realizations of $\rho$. The first three lines in equation (28) account for the evolution of incumbent banks. The demand shifter $\omega$ evolves exogenously and independently of the realization of $\rho$. Net worth evolves dependently on both the realization of $\rho$ and the banks' choice of loan rate, screening, and deposit policies. Both the demand shifter and net worth evolve independently of whether or not a new $\rho_f$ is drawn next period. The terms on the second line account for belief updating. If the bank draws a new $\rho_f$, its beliefs reset independently of the realization of $\rho$; otherwise, the realization of $\rho$ is folded into the posterior distribution. The last line in equation (28) accounts for entrants, which replace exiting banks. Entrants begin with net worth $n_e$, a demand shifter drawn from the ergodic distribution implied by $G_\omega$, and a new draw of $\rho_f$: therefore, their beliefs are consistent with the unconditional distribution of $\rho$.

### 3.2.4 Definition of equilibrium

A stationary recursive equilibrium in this environment is a list of: (i) entrepreneurial loan demands $\{L, \{L_i, \{L_{ij}(x)\}_{j\in[0,1]}\}_{i\in\{n,b\}}\}$; (ii) bank value and policy functions $\{\{V_k(x)\}_{k\in\{0,L,F\}}, \{g_y(x)\}_{y\in\{r,s,d'\}}\}$; (iii) a distribution of banks $m(x)$; and (iv) loan rate indices $\{r_L, \{r_i\}_{i\in\{n,b\}}\}$ such that

1. **entrepreneurs optimize:** taking all loan rates as given, good types solve the entrepreneurial problem in (10), (11), and (12). That is, aggregate loan demand $L$ satisfies (13), sectoral demand $L_i$ satisfies (14), and bank level demand $L_{ij}$ satisfies (15) for all banks. Bad types mimic the good types;

2. **banks optimize:** value functions and optimal policies solve the problem (18) – (27);

3. **bank distribution is stationary:** $m(x)$ is a fixed point of the operator defined in (28); and

4. **rate indices are consistent:** the bank loan rate index $r_b$ defined in (17) is consistent with the distribution $m(x)$; that is, $1 + r_b = \left[\int \omega(x)(1 + g_r(x))^{1-\phi} \mathrm{d}m(x)\right]^{\frac{1}{1-\phi}}$. The aggregate loan rate index $r_L$ is defined by (16), where $r_n = r_f + \iota_n$.

# 4 Mapping the Model to the Data

We calibrate the model in two phases. First, we assign a subset of the parameters to standard values in the literature or values directly measured from data. Second, we calibrate the remaining parameters to match a set of target moments describing key relationships in the data. The model period is quarterly.

## 4.1 Functional forms

We first describe the functional form assumptions we make in our quantitative model that are not directly implied from the analysis in Section 3. We assume that banks' equity issuance cost / dividend valuation function takes the form

$$\psi(e) = \begin{cases} e & \text{if } e \geq 0 \\ (1 + \overline{\psi})e & \text{if } e < 0 \end{cases} \tag{29}$$

where the parameter $\overline{\psi} > 0$ governs the relative costs of equity issuance. The kink at 0 in equation (29) implies an inaction region where a bank neither pays dividends nor issues equity. We assume that the screening cost function is quadratic in screening intensity:

$$c(s) = \bar{c}\frac{s^2}{2} \tag{30}$$

where $\bar{c} > 0$ governs the marginal per-unit-of-lending cost of exerting screening effort. We assume that the banks' screening technology is summarized by the function:

$$\delta(s) = \frac{\overline{\delta}s}{1 + \overline{\delta}s} \tag{31}$$

which is increasing, concave, bounded between 0 and 1, and where $\overline{\theta}$ governs the elasticity of the share of good types with respect to effective screening. We assume that the process $G_\omega$ is summarized by a mean parameter $\mu_\omega$, which we normalize to 1, as well as persistence parameter $\rho_\omega$ and standard deviation parameter $\sigma_\omega$. We discretize this process using the Tauchen method with $N_\omega$ grid points.

## 4.2 Externally assigned parameters

**Production and exogenous prices** We assume an annualized risk free rate of $r_f^a = 2\%$, consistent with the recent long run average, which implies a quarterly risk-free rate of $r_f = (1+r_f^a)^{\frac{1}{4}} - 1$. Consistent with the fact that bank deposits pay interest rates below the risk-free rate, we impose an annualized deposit liquidity premium of $\nu^a = 17$ bps: the annualized deposit rate is $r_d^a = r_f^a - \nu^a$ and the quarterly version is $r_d = (1+r_d^a)^{\frac{1}{4}} - 1$. We set the total returns to scale for the entrepreneurs' production technology to $\gamma + \eta = 0.95$, and then set $\frac{\gamma}{\gamma+\eta} = 0.4$ and $\frac{\eta}{\gamma+\eta} = 0.6$ to be consistent with 40% capital and 60% labor shares on the non-profit share of income. We set the exogenous (annualized) rental rate on capital to $\overline{r}^a = 9\%$ to be consistent with the 2% real rate and a 7% (annualized) depreciation rate, and then set the wage rate $\overline{w}$ to normalize marginal total factor costs to one.

**Bank technology and regulation** Given that the quarterly average failure rate of banks is 0.72%, and that all bank exit in the model is exogenous, we set $\pi_e = 1 - 0.0072$. Following current Basel bank regulation standards, we set the capital requirement to $\chi = 8\%$. We set the non-bank loan spread over the risk-free $\iota_n\%$ to be consistent with the average spread on Aaa-rated corporate bonds over the Treasury rate to capture an intermediation premium in this sector. We set the loss rate on loans to bad types, $\lambda$, to be consistent with an aggregate charge-off rate of 3% given our target default rate of 10%.[13]

**Bank demand process** We normalize the mean of the demand shifter process, $\mu_\omega$, to one. Motivated by our demand specification (15), we estimate log-linear regressions of the form

$$\log L_{j,t} = \alpha_j - \phi(r_{j,t} - \overline{r}_t) + \log L_t + \epsilon_{j,t}, \tag{32}$$

where $L_{j,t}$ is bank $j$'s lending at date $t$, $r_{j,t} - \overline{r}_t \approx \log(1 + r_{j,t}) - \log(1 + \overline{r}_t)$ is bank $j$'s spread over the average bank loan rate at date $t$, $\overline{r}_t = J^{-1} \sum_j r_{j,t}$, and $L_t = \sum_j L_{j,t}$ is aggregate bank lending at date $t$. Given estimated residuals $\widehat{\log \omega_{j,t}} = \alpha_j + \epsilon_{j,t}$, we then estimate

$$\widehat{\log \omega_{j,t}} = \rho_\omega \widehat{\log \omega_{j,t-1}} + \nu_{j,t}, \quad \text{where } \nu_{j,t} \sim \mathcal{N}(0, \sigma_\omega) \tag{33}$$

## 4.3 Internally calibrated parameters and targets

We discipline the remaining 11 model parameters using two sets of targets. The first set of targets are purely *cross-sectional*, consisting of first and second moments which inform banks' lending and financing policies as well as their steady state distribution across idiosyncratic states. The second set of moments may be thought of as *panel* moments, which are directly informed by the event studies around tightening events in Section 2.4. Our estimator is over-identified in the sense that

[13]This approach uses the fact that $\lambda$ may be interpreted as "loss given default" (LGD) and the default rate as "probability of default" (PD), and so the charge-off rate is PD $\times$ LGD.

Table 1: **Summary of calibration**

| **Parameter** | | **Value** | **Notes** | | |
|---|---|---|---|---|---|
| **A. Externally assigned parameters** | | | | | |
| annualized risk-free rate | $r_f^a$ | 2% | sample average ($r_f = (1 + r_f^a)^{\frac{1}{4}} - 1$) | | |
| deposit liquidity premium | $\nu^a$ | 0.17% | sample average, CITE ($r_d^a = r_f^a - \nu^a$) | | |
| annualized rental rate | $\overline{r}^a$ | 9% | 2% interest + 7% depreciation, $\overline{r} = (1 + \overline{r}^a)^{\frac{1}{4}} - 1$ | | |
| wage rate | $\overline{w}$ | 3.78 | normalize total factor costs to 1 | | |
| capital share | $\gamma$ | 0.38 | capital share = 40% (given 5% profit share) | | |
| labor share | $\eta$ | 0.57 | labor share = 60% (given 5% profit share) | | |
| bank survival probability | $\pi_e$ | 99.28% | sample average, quarterly bank failure rate | | |
| capital requirement | $\chi$ | 8% | Basel minimum | | |
| mean demand shifter | $\mu_\omega$ | 1.0 | normalization | | |
| non-bank loan premium | $\iota_n$ | 1.5% | maturity-adjusted Aaa spread over Treasury rate | | |
| loss given default | $\lambda$ | 0.1 | charge-off rate = 3% | | |
| persistence, demand shifter | $\rho_\omega$ | 0.9 | directly estimated | | |
| std. dev, demand shifter | $\sigma_\omega$ | 0.5 | directly estimated | | |
| **B. Internally calibrated parameters** | | | | | |
| | | | **Target** | **Data** | **Model** |
| pop. share of good types | $\mu_\rho$ | 0.9 | default rate | 10% | |
| std. dev. of fundamental $\rho_f$ | $\sigma_{\rho_f}$ | 0.1 | cross-bank dispersion in default rates | 2.0% | |
| std. dev. of noise $\rho_n$ | $\sigma_{\rho_n}$ | 0.1 | event study, loan originations | see figure X | |
| prob. draw new $\rho_f$ | $\pi_{\rho_f}$ | 0.1 | event study, loan rates | see figure X | |
| elasticity, screening tech. | $\overline{\delta}$ | 1.0 | non-interest expense ratio | 4.6% | |
| working capital parameter | $\kappa$ | 1.0 | business debt to GDP ratio | 71.5% | |
| screening cost function | $\overline{c}$ | 0.2 | net dividend payouts / NW | 5.8% | |
| equity issuance cost | $\overline{\psi}$ | 0.2 | gross equity issuance / NW | 1.1% | |
| elasticity between banks | $\phi$ | 2.0 | mean net interest margin | 3.5% | |
| elasticity between sectors | $\varepsilon$ | 1.5 | std. dev.net interest margin | 1.5% | |
| non-bank demand weight | $\zeta_n$ | 0.1 | bank share of debt | 40.0% | |
| | | | average bank leverage | 88.7% | |

**Notes:**

the number of target moments (26) exceeds the number of parameters (11). We describe each set of targets in turn, as well as their relationships to key parameters in the model, though of course all parameters in this model are jointly determined.

**Cross-sectional moments** As discussed in Section 2.5, our model is designed to allow for two margins of adjustment by banks: pricing (via the loan rate $r$) and approvals (via screening intensity $s$). These margins directly inform banks' profitability and risk profiles, and so in order for our model to provide a suitable quantitative laboratory, it must generate realistic outcomes along both these dimensions. The other key decision banks' make is how they finance the loans they make. Although this has been less of an explicit focus of our analysis to this point, generating realistic financing patterns is critical to ensure that our model performs well along the aforementioned profitability and risk dimensions, since both these choices interact with financial constraints.

Panel B of Table 1 includes 8 moments which summarize banks' profitability, riskiness, and financing patterns. In terms of profitability, we target banks' average net interest margin (NIM), as well as the average cross-sectional dispersion in NIM. Banks' NIMs reflect both default risk premia and market power. In an environment with monopolistic competition and heterogeneity in the (endogenous) degree of financial constraints like ours, then, these moments help inform both the distribution of borrower risk (e.g. parameters like $\mu_\rho$ and $\sigma_\rho^2 = \sigma_{\rho_f}^2 + \sigma_{\rho_n}^2$) and the degree of substitutability both within the banking sector and between the bank and non-bank sectors (e.g. parameters such as $\phi$, $\varepsilon$, and $\zeta_n$). We take a similar approach for the default rate, targeting both the average and the dispersion across banks, further informing the parameters which govern the distribution of risk in the economy. To discipline banks' financing policies, we target the average level of bank leverage (which in turn pins down the average capital buffer on top of the minimum required by regulation), as well as banks' net dividend payout and gross equity issuance policies, which discipline banks' net worth retention and the costs of issuing equity.

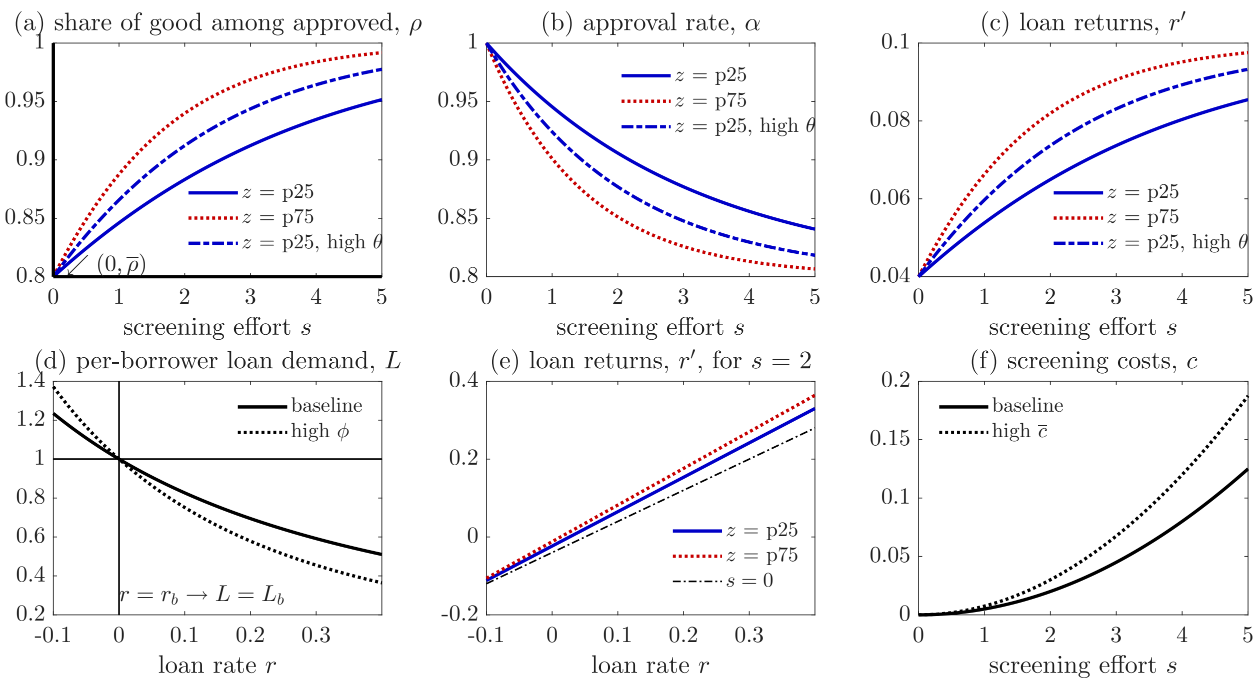
We target three additional cross-sectional moments. The overall business debt to GDP ratio helps inform the level of loan demand, which is intimately connected to the working capital parameter $\kappa$. Insofar as screening in our model requires a flow investment of financial resources, our model has a meaningful source of non-interest expenses, and so we discipline this margin by matching the average non-interest expense to loan ratio in the data. Finally, the bank share of debt helps inform the relative competitiveness of the non-bank sector.

**Panel moments** Our model is designed to be able to match the patterns in Section 2.4, but does not impose them. For example, the speed at which banks adjust their standards in response to observations of loan performance depends critically on the speed of learning, which depends on both the dispersion in fundamentals $\sigma_{\rho_f}$ and the share of total variance in loan performance due to fundamentals, $\frac{\sigma_{\rho_f}^2}{\sigma_{\rho_f}^2+\sigma_{\rho_n}^2}$. Similarly, the change in performance in a bank's loan portfolio after tightening may be fast or slow depending on how large the costs of screening are ($\bar{c}$) or how effective screening is ($\bar{\delta}$). We allow the data to inform these parameters.

In principle, the results presented in Section 2.4 offer discipline on profitability (e.g. rates and origination volumes) and risk (e.g. non-performing loan and charge-off rates). We focus on the former category because of an important conceptual gap between our model and the data: loan contracts in the data are *long-term*, while loan contracts in our model are *one-period*. This assumption is made for tractability: as a bank learns over time about its loan pool, it will adjust its standards, and tracking the distribution of loan risk in order to make further inference and respond appropriately becomes quite complicated. In the data, then, loan performance after a tightening or easing episode still reflects the performance of loans made before the episode, which is not the case in our model.

This gap between model and data does not arise, however, when we consider either the volume of new loan originations or the interest rates on those new loans, which are precisely the objects

Figure 8: **Visualizing model technologies**




measured in Figure 4. Therefore, we estimate the same regressions and compare our point estimates to those from the data at horizons of ±1 quarter relative to a tightening event.

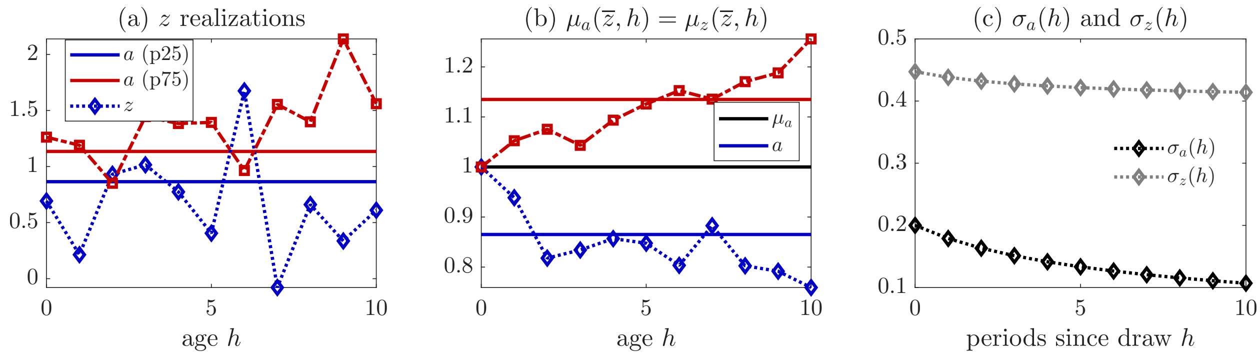
### 4.4 Results and model validation

**Approvals and loan demand** Figure 8 helps visualize the model technologies. Panel (a) plots the share of good borrowers in the approved loan pool as a function of screening effort $s$. Note that having higher $z$ or a higher elasticity parameter $\theta$ leads to a higher share of good borrowers. The approval rate in panel (b) is the flipside of this: banks attain a higher share of good borrowers by lowering their approval rate. Panel (c) shows that loan returns mirror the share of good borrowers in panel (a). Turning to the demand side, panel (d) shows the loan demand system, a simple CES structure. Panel (e) shows that loan returns increase in the loan rate, and more so the higher is the share of good borrowers in the pool. Lastly, panel (f) simply represents the quadratic screening technology.

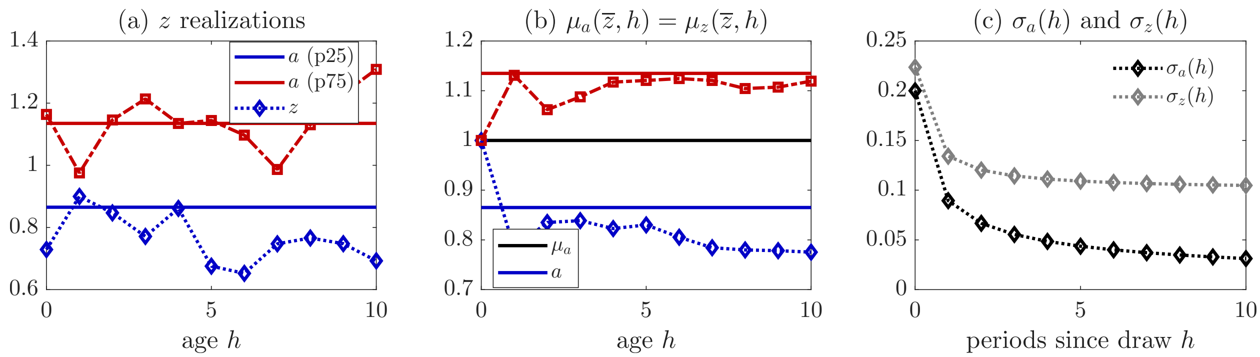
**Learning dynamics** Figure 9 simulates paths of bank-level return shocks in order to highlight how beliefs evolve in the model. In each figure, we consider 2 banks who draw a new persistent component of screening ability $a$ at age 0 and realize $z$ shocks for 10 periods thereafter. One bank has the fundamental $a$ towards the top of the distribution, while the other has a lower fundamental.

We consider 2 cases. First, panel (a) considers the case when screening ability is quite noisy in the sense that the variance of the transitory shocks $b$ far exceeds the variance of the persistent shocks $a$: that is, $\sigma_b > \sigma_a$. In this case, the fundamental difference between the two banks is small

Figure 9: **Learning dynamics in the model: simulations**




(a) **Noisy**

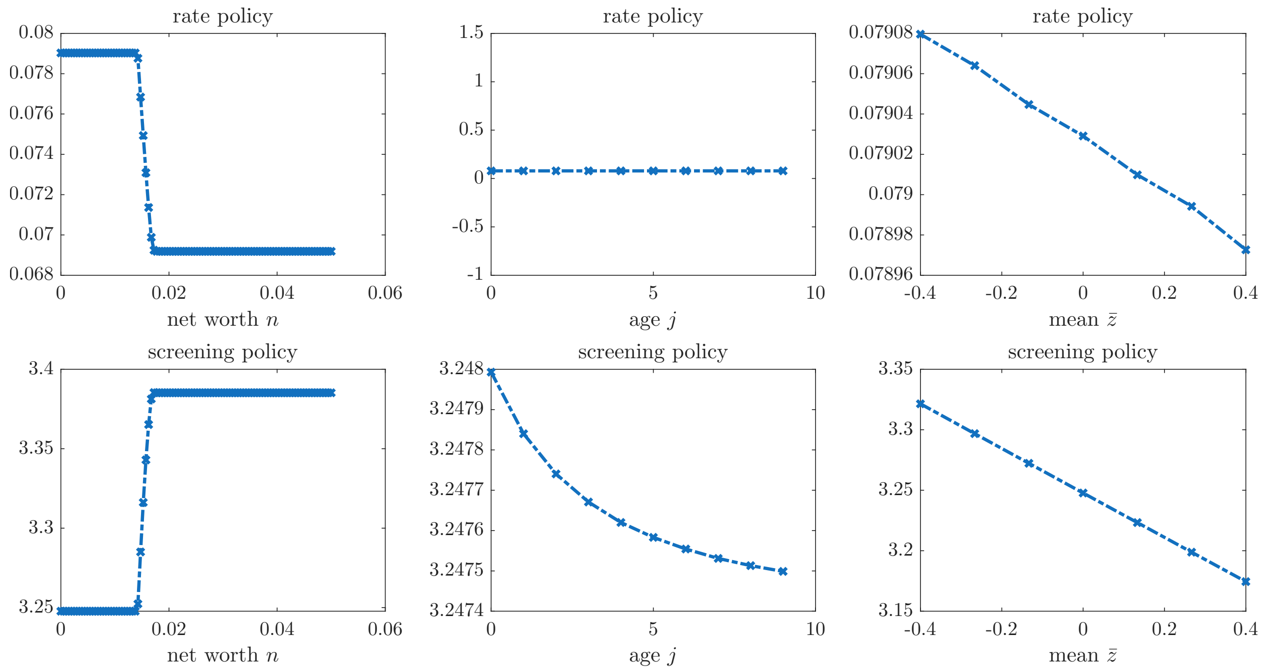



(b) **Precise**

relative to the noise. As panel (a) shows, the realizations of $z$ regularly "cross," which leads the evolution of the posterior to be slower and less precise in panel (b). Notably, in this example, the posterior does not necessarily "settle down" at the fundamental over the simulation period. As shown in panel (c), the result is that uncertainty about the distribution of $z$ remains elevated both because the fundamental uncertainty is high due to $b$, and because the posterior over $a$ does not become tight.

Turning to the lower set of panels (b), we see that the situation is quite different when the inference problem that banks face is less difficult. In this case, the differences in screening ability across banks are driven primarily by the fundamental component, $a$. Even a quick glance at panel (a) reveals that the $z$ realizations are very easy to separate between these two banks. As a result, turning to panel (b), we see that the posteriors quickly get close to the truth, and tend to stay near it once they do. This is reinforced in panel (c), where we observe a sharp downward slope in the variances $\sigma_a(h)$ and $\sigma_z(h)$ with respect to $h$. Ultimately, using our micro data from Section 2 to quantitatively discipline the learning process in the model will be an important step.

Figure 10: **Policy functions**




## 5 Quantitative Analysis

In this section, we first describe the mechanics of the model and evaluate its empirical performance along key cross-sectional dimensions. We then validate the model by revisiting our main empirical findings in the context of the model.

### 5.1 Model mechanics and key cross-sectional moments

As a first step towards understanding the key economic forces in our model, Figure 10 plots the key loan policy functions for banks over the state space in our quantitative model. Panels (a) through (c) correspond to rate setting, while panels (d) through (f) correspond to the choice of screening.

Beginning with rate setting policy, we first see the familiar result that the optimal interest rate is weakly decreasing in bank net worth: as the banks get away from financial constraints associated with low net worth, the lower interest rates in order to increase their loan base. The other two panels in the top row reveal that rate setting is not sensitive to the state variables which form the bank's posterior beliefs over its screening ability, consistent with our empirical evidence.

The bottom three panels consider the screening policy. The left panel reveals an important complementarity between screening and rate setting: as banks cut rates to expand their lending bases, they optimally incur greater screening costs in an effort to ensure that they have a more creditworthy borrower pool. Unlike rate policies, however, screening policies are in fact sensitive to the posterior beliefs of the bank, particularly the posterior mean $\bar{z}$. This result is intuitive: banks who have discovered – after observing low returns on their loans in prior periods – that they are bad at screening out borrowers will optimally choose to invest more in screening. Looking ahead to the empirical validation of our model, it is precisely this force which leads to the backward-looking tightening dynamics we observe in the data.

### 5.2 Model validation

We perform two key analyses: We first simulate paths of choices for banks who receive adverse realizations of loan returns, controlling for fundamentals. Then, we run an analogous exercise with a negative shock to loan demand in order simulate an increase in competition through the lens of the model. Each experiment is described in turn, followed by a discussion of the resulting adjustment paths and their alignment with the data.

#### 5.2.1 Tightening in the wake of negative return realizations

In order to highlight that our model delivers the mechanism documented in our empirical analysis, we simulate a panel of banks and measure the elasticity of screening responses with respect to negative return realizations along the equilibrium path. Notably, this elasticity can be measured without appealing to an aggregate shock. At the same time, though, its measurement depends on a wide range of factors in our baseline model environment, such as the financial health of the lender and the tightness of the bank's posterior beliefs over its screening ability.

#### 5.2.2 Easing in the face of an increasing in competition

TBA

## 6 Application: Thoughts on the SVB episode

The banking stress episode of March 2023 provides a natural application of our framework and highlights the value of both our novel credit supply index and the model.

With respect to measurement, the episode highlights a key limitation of aggregate diffusion indices. While the standard diffusion measure indicates a broad-based contraction in credit supply, it obscures substantial heterogeneity across banks. In contrast, our bank-level credit supply index preserves cross-sectional variation in lending behavior. Using the most recent SLOOS data, we document a pronounced divergence in lending standards across bank types, with regional banks—those with assets between $50 and $250 billion—tightening significantly more than large banks. The Silicon Valley Bank (SVB) episode therefore provides external validation that our index captures economically meaningful shifts in credit availability at the institution level, even when aggregate indicators evolve more smoothly.

Although the empirical analysis in the paper focuses on data through 2019, extending the index through the SVB episode confirms that a substantial share of relevant information about credit supply adjustments resides in the cross-section rather than in the aggregate. During periods of stress, variation in individual banks' responses reflects systematic differences in exposure to funding pressures and balance-sheet constraints, rather than transitory noise. These are precisely the dimensions along which aggregation into a diffusion index masks economically important dynamics.

The episode also underscores the need for a structural model. While the data establish that regional banks tightened more than large banks, they do not speak to the mechanisms underlying this divergence. Our model provides a mechanism-based interpretation by emphasizing heterogeneity in banks' vulnerabilities. More vulnerable banks—those experiencing deposit outflows and heightened balance-sheet strain—face stronger incentives to tighten lending standards. In the model, tightening operates through an increase in screening intensity, which both reduces exposure to low-return borrowers and frees up balance-sheet capacity. These forces are especially valuable for banks operating near capital or liquidity constraints, generating a pronounced tightening response. By contrast, less vulnerable banks, which experience deposit inflows and are better insulated from stress, are able to absorb shocks with relatively smaller adjustments to screening and lending policies.

Viewed through the lens of the model, the SVB episode illustrates how differences in balance-sheet conditions translate into heterogeneous credit supply responses. While the data document divergence in lending standards across bank types, the model clarifies the economic forces that generate these patterns. Together, the credit supply index and the model provide a coherent interpretation of the banking stress episode: credit supply contracted unevenly because banks differed in their exposure to stress, and these differences shaped the incentives governing lending and screening decisions.

# 7 Conclusion

This paper develops a new, comprehensive measure of bank credit supply and uses it to clarify the drivers, margins, and consequences of changes in lending policies. By combining confidential SLOOS microdata with Call Reports and Y-14Q supervisory data, we document that credit-supply tightening operates primarily through quantities rather than prices: banks that tighten raise loan-rate spreads only modestly, while C&I originations and balances decline substantially and persistently. These effects are not primarily explained by large changes in observable loan characteristics, pointing to an approval or screening margin that is difficult to observe directly in loan-level data.

We also document a systematic asymmetry in the drivers and margins of adjustment. Banks tighten in response to deteriorating borrower risk and loan performance, while they ease primarily in response to competitive pressures; risk-driven tightening is broad-based, whereas competition-driven easing is concentrated more strongly in price terms. A quantitative general equilibrium model of bank lending with learning, screening, bank and nonbank competition, and financial frictions accounts for these patterns and provides a framework for decomposing credit-supply dynamics into distinct supply mechanisms — screening, pricing, learning, competition, and balance-sheet channels. Taken together, our results provide a disciplined interpretation of lending standards as a well-defined economic object and demonstrate their central role in shaping credit dynamics.

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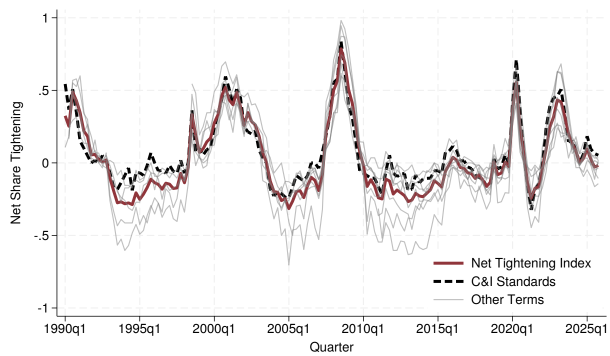
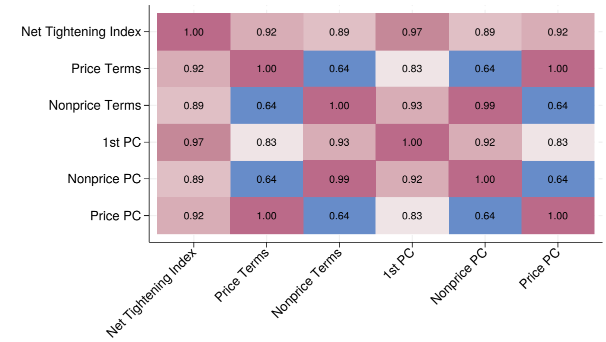
# Appendix: "Bank Credit Supply: Measurement and Implications"

## A Data Appendix

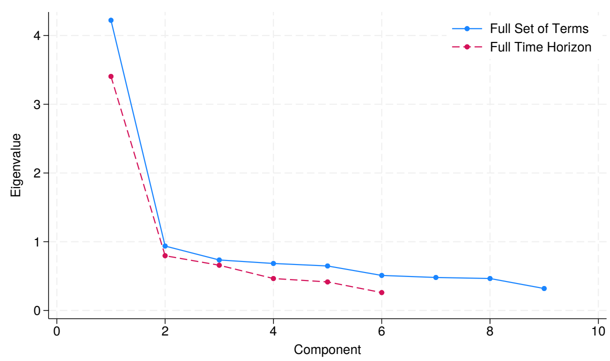
Figure A.1: **Additional Detail on Net Tightening Index**



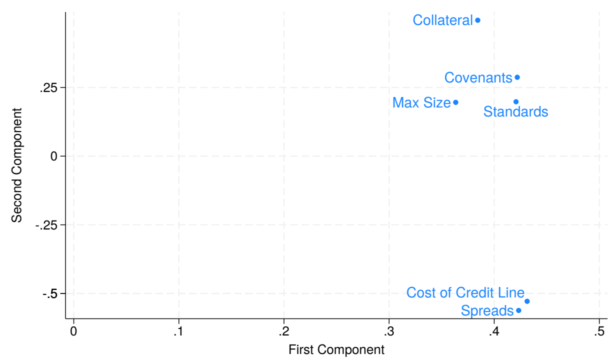

(a) Supply Measures over Time




(b) Histogram of Tightening Responses



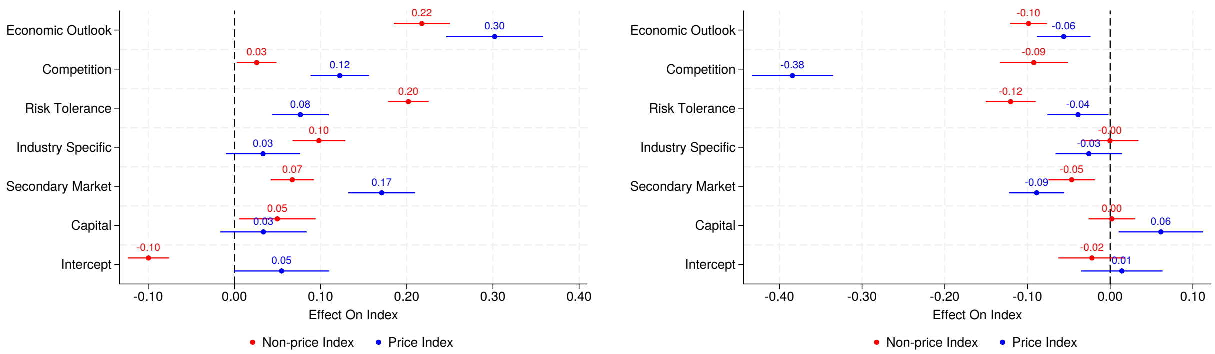

(c) Scree Plots




(d) Loading for Longer Time series

**Notes:** Panel (a) plots averages across banks within a quarter for the tightening index (red), the net change in standards (black) and the net change in other terms (grey), over time. Panel (b) presents a correlation matrix between the net tightening index, the Price and Non-price indexes, the first principal component for the net change in various loan terms, and the principal components associated with non-price terms when doing pca with varimax rotation. Panel (c) presents scree plots, representing the variation accounted for by each component, when doing pca on the fuller set of terms covered in SLOOS (blue) and the smaller set of terms needed to cover the full timeseries (red). Panel (d) presents the loading plot associated with pca on this smaller set of terms. **Source:** SLOOS.

Figure A.2: **Motivations for Changing Price and Nonprice terms**

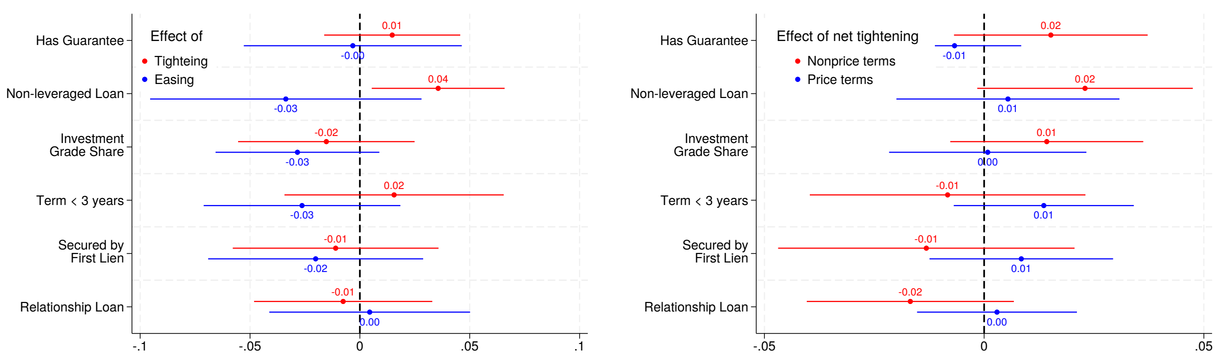



(a) Reasons for tightening

(b) Reasons for easing

**Notes:** This presents coefficient estimates from predicting the tightening index for price and nonprice terms (red and blue dots, respectively) on dummies for banks' self-reported reasons for changing standards. In the left panel, independent variables are dummies for whether banks reported a given reason was important in motivating banks to tighten standards or terms (for the set of banks that tightened along some-such dimension). The right panel presents equivalent estimates for the effects of citing a reason as important for easing. Lines present 90% confidence intervals for standard errors that are clustered by quarter.
**Sources:** SLOOS.

Figure A.3: **Asymmetric Effects on Terms**




(a) Tightening vs Easing

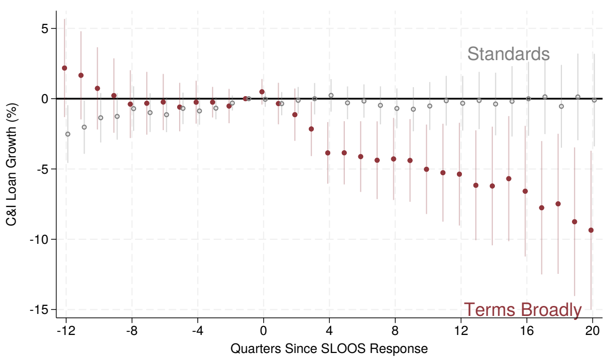
(b) Price vs. Non-price terms

**Notes:** This presents $\beta$ and $\eta$ estimates from:

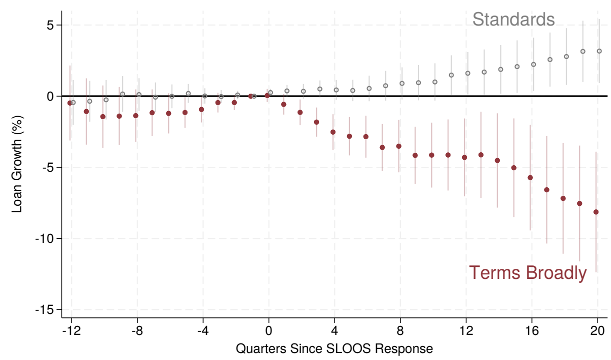
$$y_{b,t+1} - y_{b,t-1} = \beta \text{Tightening Index}_{b,t} + \eta \text{Easing Index}_{b,t} + \Gamma \mathbf{X}_{b,t} + \tau_t + \epsilon_{b,t}$$

The right chart presents estimates replacing the independent variables of interest with Price index$_{b,t}$ and Non-price index$_{b,t}$, reflecting the net share of price and non-price terms a bank reports as tightening. $y$ is the share of loan originations that (i) have full or partial guarantees from a guarantor, (ii) are not classified as leveraged loans, (iii) have an investment grade internal risk rating (BBB or better), (iv) have a loan term under 3 years, (v) are secured by a first lien on collateral, and (vi) are to a borrower for which there is a record of previous borrowing in the Y-14. Standard errors are clustered by quarter.
**Sources:** SLOOS, Y-14.

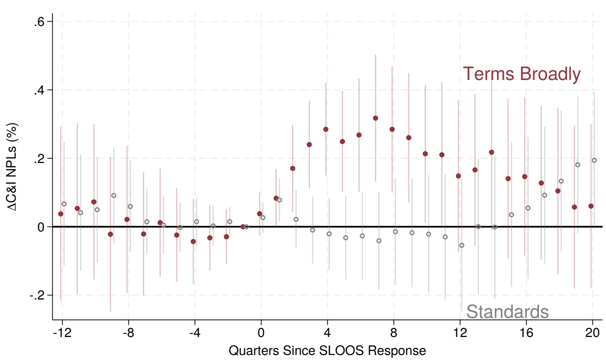
Figure A.4: **Trends in Portfolios Around a Change in Supply, Controlling for Standards**



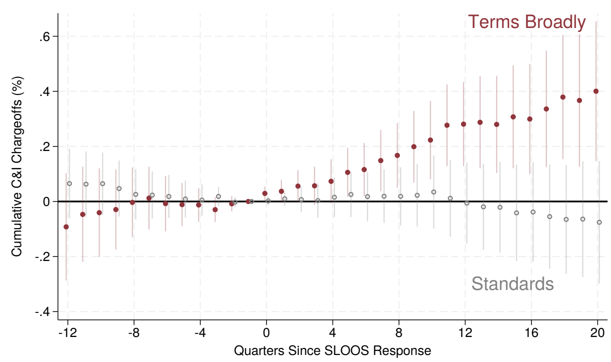

(a) Change in C&I loan balances




(b) Change in Total loan balances



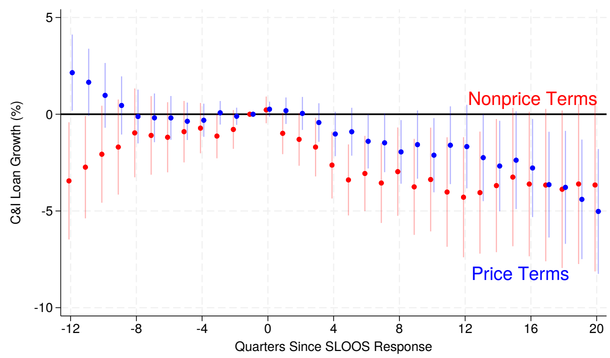

(c) Change in C&I Nonperforming Loan Rate



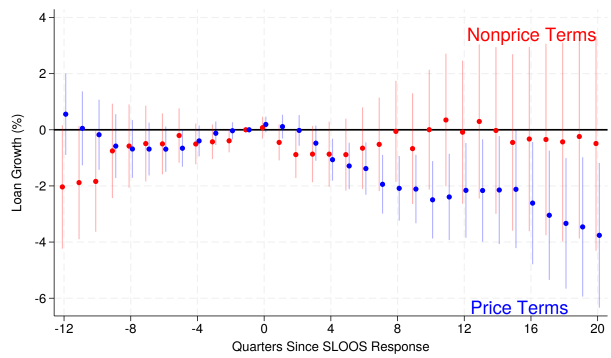

(d) Cumulative C&I Net Charge-offs

**Notes:** This figure plots the regression coefficients from (1) by time horizon $h$, but adding a control for the net tightening in C&I loan standards. Each figure plots estimates and 90% confidence intervals for $\{\beta^h\}$ (in red) and estimates for the coefficient on the net tightening in standards (in grey). $y$ is ln(C&I Loan Balances) in a, ln(Total Loan Balances) in b, the C&I loan nonperforming loan rate in c, and cumulative C&I loan charge-offs in d. The sample covers the period from 1990 to 2025.
**Sources:** Call Reports, SLOOS.

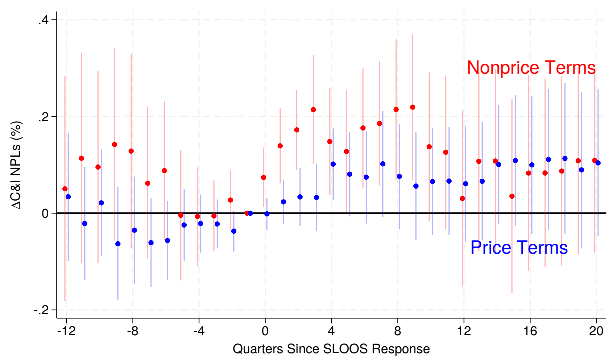
Figure A.5: **Trends in Portfolios Around a Change in Supply, Asymmetry in Price and non-Price terms**



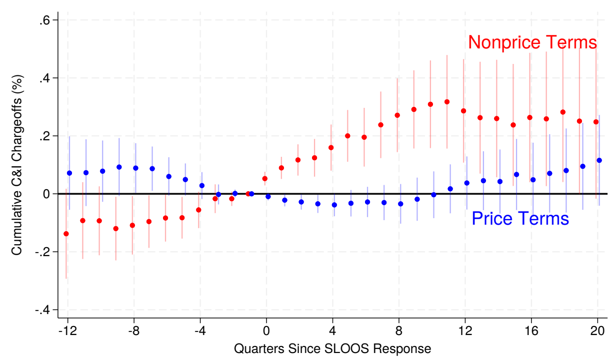

(a) Change in C&I loan balances




(b) Change in Total loan balances




(c) Change in C&I Nonperforming Loan Rate




(d) Cumulative C&I Net Charge-offs

**Notes:** This figure plots the regression coefficients from (1) by time horizon $h$, but with Price index and Non-price index appearing in place of Net Tightening index. Each figure plots estimates and 90% confidence intervals for the coefficient on Price index (blue) and Non-price index (red), where $y$ is ln(C&I Loan Balances) in a, ln(Total Loan Balances) in b, the C&I loan nonperforming loan rate in c, and cumulative C&I loan charge-offs in d. The sample covers the period from 1990 to 2025.
**Sources:** Call Reports, SLOOS.

# B Model Appendix

## B.1 Analysis of entrepreneur problem

**Aggregate demand** Placing multiplier $\lambda$ on the working capital constraint, the first order conditions of problem (10) are:

$$\begin{aligned} f_k(k,n) &= g_k(k,n)(1+\lambda\kappa) \\ f_n(k,n) &= g_n(k,n)(1+\lambda\kappa) \\ \lambda &= \frac{1+\tilde{r}}{1+r_f}-1 \end{aligned}$$

Dividing through the first two conditions and plugging in our functional forms yields $n = \frac{\overline{r}\eta}{\overline{w}\gamma}k$, which implies that $f(k,n) = \left(\frac{\overline{r}\eta}{\overline{w}\gamma}\right)^{\eta} k^{\gamma+\eta}$ and $g(k,n) = \overline{r}\frac{\gamma+\eta}{\gamma}k$. Plugging these expressions into the first optimality condition yields

$$1+\lambda\kappa = \frac{(\gamma+\eta)\left(\frac{\overline{r}\eta}{\overline{w}\gamma}\right)^{\eta} k^{\gamma+\eta-1}}{\overline{r}\frac{\gamma+\eta}{\gamma}} \qquad \Longrightarrow \qquad k = \left[\frac{\left(\frac{\gamma}{\overline{r}}\right)^{1-\eta}\left(\frac{\eta}{\overline{w}}\right)^{\eta}}{1+\lambda\kappa}\right]^{\frac{1}{1-\gamma-\eta}}$$

Plugging the expression for $\lambda$ from the third first order condition, recognizing that the working capital constraint binds, and rearranging terms yields the expression in (13).

**Sector-specific demand** Setting $\zeta_n = \zeta$ and $\zeta_b = 1-\zeta$ and placing multiplier $\lambda$ on the constraint, the first order condition of the sectoral cost minimization problem (14) with respect to demand from sector $i$ is

$$\begin{aligned} 1+r_i &= \lambda\frac{\varepsilon}{\varepsilon-1}\left[\sum_i \zeta_i^{\frac{1}{\varepsilon}} L_i^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}-1} \zeta_i^{\frac{1}{\varepsilon}}\frac{\varepsilon-1}{\varepsilon}L_i^{\frac{\varepsilon-1}{\varepsilon}-1} \\ &= \lambda\left[\sum_i \zeta_i^{\frac{1}{\varepsilon}} L_i^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{1}{\varepsilon-1}} \zeta_i^{\frac{1}{\varepsilon}} L_i^{-\frac{1}{\varepsilon}} \\ \Longrightarrow L_i &= \zeta_i\left(\frac{1+r_i}{\lambda}\right)^{-\varepsilon} L \end{aligned}$$

where the last line recognizes that the constraint binds. Plugging the expression above back into the sectoral CES aggregator allows us to solve for $\lambda$ as the aggregate rate index (16), and plugging this rate index back into the expression above yields the sectoral demand curve in (14).

**Bank-specific demand** We proceed similarly to the sectoral demand problem above. The first order condition of problem (12) with respect to loans from a given bank $j$ is

$$\begin{aligned}
1 + r_j &= \lambda \frac{\phi}{\phi - 1} \left[ \int_0^1 \omega_j^{\frac{1}{\phi}} \ell_j^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1} - 1} \omega_j^{\frac{1}{\phi}} \frac{\phi - 1}{\phi} \ell_j^{\frac{\phi-1}{\phi} - 1} \\
&= \lambda \left[ \int_0^1 \omega_j^{\frac{1}{\phi}} \ell_j^{\frac{\phi-1}{\phi}} \right]^{\frac{1}{\phi-1}} \omega_j^{\frac{1}{\phi}} \ell_j^{-\frac{1}{\phi}} \\
\implies \ell_j &= \omega_j \left( \frac{1 + r_j}{\lambda} \right)^{-\phi} L_b
\end{aligned}$$

where the last line imposes the binding constraint. Plugging the expression above back into the banking sector CES aggregator allows us to solve for $\lambda$ as the sectoral rate index (17), and plugging this rate index back into the expression above yields the bank-specific demand curve in (15).

## B.2 Analysis of bank problem

The budget constraint, net worth accumulation equation, and belief updating equation must hold with equality at any optimum. Therefore we can simplify the bank's problem into

$$\begin{aligned}
V(n, \omega, \overline{z}, j) &= \max_{s,r,d'} \psi \left( n + d' - c(s)\ell(r;\omega) \right) \qquad \text{(B.1)} \\
&\quad + \frac{1}{1 + r_f} \mathbb{E}_z \left[ W \left( (1 + \mathcal{R}(r, s; z))\ell(r;\omega) - (1 + r_d)d', \omega, \frac{j\overline{z} + z}{j + 1}, j + 1 \right) \mid \overline{z}, j \right] \\
\text{subject to:} &\quad d' \leq (1 - \chi)\ell(r;\omega)
\end{aligned}$$

Placing multiplier $\mu$ on the capital requirement, a solution with positive lending, screening, and deposits must satisfy the following first order conditions with respect to $r$, $s$, and $d'$, respectively:[14]

$$\begin{aligned}
\psi'(e)c(s)\frac{\partial \ell}{\partial r} &= \frac{1}{1 + r_f} \mathbb{E}_z \left[ \left( (1 + \mathcal{R}(r, s; z))\frac{\partial \ell}{\partial r} + \frac{\partial(1 + \mathcal{R})}{\partial r}\ell \right) W_n'(z; r, s, d') \right] + \mu(1 - \chi)\frac{\partial \ell}{\partial r} \qquad \text{(B.2)} \\
\psi'(e)\frac{\partial c}{\partial s}\ell &= \frac{1}{1 + r_f} \mathbb{E}_z \left[ \frac{\partial(1 + \mathcal{R})}{\partial s} \ell W_n'(z; r, s, d') \right] \qquad \text{(B.3)} \\
\psi'(e) &= \frac{1 + r_d}{1 + r_f} \mathbb{E}_z \left[ W_n'(z; r, s, d') \right] + \mu \qquad \text{(B.4)}
\end{aligned}$$

where we have simplified notation by defining $W_n'(z; \cdot) = \frac{\partial W(n'(z), \omega, \overline{z}'(z), j+1)}{\partial n}$, suppressing the explicit dependence of the expectation with respect to $z$ on $\overline{z}$ and $j$, and other similar transformations.

[14]If any of these is zero there is an additional multiplier, but these cases are less relevant to the economics at the heart of the model.

**Optimal rate setting** We define the elasticity of $x$ with respect to $y$ as $\epsilon_{x,y}$. Then, dividing through by $\frac{\partial \ell}{\partial r}$ in (B.2) and simplifying elasticity terms yields the expression

$$c(s) = \mathbb{E}_z \left[ \underbrace{\frac{1}{1+r_f} \frac{W_n'(z;r,s,d')}{\psi'(e)}}_{\text{bank "SDF"}} \times \underbrace{\left(1 + \frac{\epsilon_{1+\mathcal{R},r}(z)}{\epsilon_{\ell,r}}\right)(1+\mathcal{R}(r,s;z))}_{\text{marginal return from raising } r} \right] + \mu \frac{1-\chi}{\psi'(e)} \tag{B.5}$$

For intuition, suppose the capital requirement is slack so that $\mu = 0$. Then, equation (B.5) has a natural interpretation: the marginal cost of lending ($c(s)$) must equal the expected discounted marginal return from lending. Here, the discounting reflects the fact that the bank may weight different future states (realizations of $z$) differently in the presence of financial constraints, and the marginal return (for a given $z$) reflects the tradeoff between the bank's market power ($\epsilon_{\ell,r} < 0$) and increasing the returns earned from good borrowers ($\epsilon_{1+\mathcal{R},r}(z) > 0$ from equation (6)). If the capital requirement binds so that $\mu > 0$, then the marginal cost will exceed the marginal return; that is, the bank will set $r$ higher than if the capital requirement were slack to lower its loan demand and therefore its funding burden.

**Optimal screening** We can proceed similarly to analyze the screening intensity choice problem, obtaining the following version of (B.3):

$$\epsilon_{c,s} c(s) = \mathbb{E}_z \left[ \frac{1}{1+r_f} \frac{W_n'(z)}{\psi'(e)} \times \epsilon_{1+\mathcal{R},s}(z)(1+\mathcal{R}(r,s;z)) \right] \tag{B.6}$$

That is, the marginal cost of screening must equal the expected discounted marginal return from screening. Since there is no loan demand effect from screening, whether or not the capital requirement binds is not directly relevant, except through the bank-level SDF term (which appears in each of the bank's optimality conditions).

**Financing considerations** Analyzing the optimality condition with respect to deposits (B.4) sheds light on the financing side of the bank problem:

$$\frac{1}{1+r_d} = \mathbb{E}_z \left[ \frac{1}{1+r_f} \frac{W_n'(z)}{\psi'(e)} \right] + \frac{1}{1+r_d} \frac{\mu}{\psi'(e)} \tag{B.7}$$

If the capital requirement is slack, the marginal cost of funds is equal to the deposit rate and so the bank discounts the future at the deposit rate. Otherwise, the discount rate exceeds the deposit rate, reflecting the fact that funds are relatively more valuable to the bank today then they are expected to be in the future.

To further understand the bank's discount factor, it is useful to compute the marginal value term $W_n'(z)$ using equation (18) together with the envelope condition $V_n(n,\omega,\bar{z},j) = \psi'(e(n,\omega,\bar{z},j))$:

$$W_n(n,\omega,\bar{z},j) = (1-\pi_e)\psi'(n) + \pi_e \mathbb{E}_{\omega'} \left[ (1-\pi_a)\psi'(e(n,\omega',\bar{z},j)) + \pi_a \psi'(e(n,\omega',\mu_a,0)) \right] \tag{B.8}$$

So the marginal value of wealth at the start of the period is equal to the weighted average marginal valuation of dividends.

Assuming the functional form in (29) below, (B.8) implies that $\mathbb{E}_z[W_n'(z)] \in [1, \overline{\psi}]$ and $\psi'(e) \in \{1, \overline{\psi}\}$. Further, in the presence of a liquidity premium on deposits, $\overline{r}^d < \overline{r}$, and so $\overline{q}(1+\overline{r}^d) < 1$. Then, if the capital requirement is slack ($\mu \leq 0$), (B.7) implies that $\psi'(e) < \mathbb{E}_z[W_n'(z)] \leq \overline{\psi}$, and so we must have $\psi'(e) = 1$; therefore, the bank cannot be issuing equity today ($e \geq 0$). *If the capital requirement is slack, then the bank does not issue equity. By contrapositive, if the bank issues equity, then the capital requirement must bind.* This result can be useful for computational efficiency, even though it is still possible that the capital requirement binds and the bank pays a dividend.

### B.3 Full information bank problem

A useful case of the model to consider to highlight the role of the information friction is the "full information" case, which we define to be the case in which the bank directly observes the persistent component of its screening effectiveness, $a$. In this case, there is no learning, and so no need for Bayesian updating. However, there is still some residual uncertainty on screening effectiveness due to the transitory component, $b$.

At the beginning of the period, then, the analogous value function to (18) is

$$W(n, \omega, a) = (1 - \pi_e)\psi(n) + \pi_e \mathbb{E}_{\omega'}\left[(1 - \pi_a)V(n, \omega', a) + \pi_a \int V(n, \omega', a')\mathrm{d}G_a(a') \mid \omega\right] \tag{B.9}$$

There are two main differences between (B.9) and (18). First, the state variables $\overline{z}$ and $j$ are replaced by $a$, which is now assumed to be directly observable. Second, in the case in which a new $a$ is drawn, we now integrate over the possible values of $a$, since the bank will learn the realization of its new draw, not simply that it received a new draw.

Turning to the lending phase, the problem becomes:

$$V(n, \omega, a) = \max_{e,s,r,d',n'} \psi(e) + \frac{1}{1 + r_f} \int W(n', \omega, a)\mathrm{d}G_b(b) \tag{B.10}$$

$$\text{subject to:} \quad n' = n'(r, s, d'; a, b) = (1+)\mathcal{R}(r, s; a, b)\ell(r; \omega) - (1 + r_d)d' \text{ for all } b \tag{B.11}$$

as well as the budget constraint (25) and the capital requirement (26), which are unchanged from the baseline model. The key differences from the benchmark case for this problem are that the distribution over which continuation values are evaluated is simply the distribution of the $b$ shock and that there is no belief updating.

### B.4 Functional forms and elasticities

We assume a constant elasticity of substitution specification for loan demand so that $\epsilon_{\ell,R} = -\phi$ always. Moreover, equation (6) implies that $\mathcal{R}(R, s; z) = 1 - \lambda + (R - (1 - \lambda))\rho(\xi(s, z))$ so that

$\frac{\partial \mathcal{R}}{\partial R} = \rho(\xi)$, and so $\epsilon_{\mathcal{R},R} = \frac{\partial \mathcal{R}}{\partial R}\frac{R}{\mathcal{R}} = \frac{R\rho(\xi)}{1-\lambda+(R-(1-\lambda))\rho(\xi)}$.

Turning to the screening side, it is easier to work directly with partial derivatives rather than elasticities. In terms of returns, $\frac{\partial \mathcal{R}}{\partial s} = (R-(1-\lambda))\frac{\partial \rho}{\partial \xi}\frac{\partial \xi}{\partial s}$, and the marginal effect of effective screening on the share of good borrowers is

$$\frac{\partial \rho}{\partial \xi} = (-1)\left(\frac{1}{1+\exp\{-\eta(\xi-\overline{\xi})\}}\right)^2 \cdot (-\eta)\cdot \exp\{-\eta(\xi-\overline{\xi})\} = \eta\rho(\xi)(1-\rho(\xi))$$

which implies that $\epsilon_{\rho,\xi} = \eta\xi(1-\rho(\xi))$. This means that it could be easiest to use a root finding algorithm for the optimal screening choice if the problem is sufficiently smooth, but that may not be the most stable.

### B.5 Computational algorithm

1. **Preliminaries.** Set all model parameters and define grids for the 4 idiosyncratic bank state variables $(n, \omega, \overline{z}, j)$.

    - *Grids.* Choose the $n$ grid exogenously. Choose the $\omega$ grid using a standard method like Tauchen. Choose the $\overline{z}$ grid to be $\pm$ a fixed number of standard deviations around $\mu_a$. Finally, choose the $j$ grid upper bound such that $\mathbb{P}(j > \overline{j}) < \varepsilon_j$, a prespecified parameter. Make the $\omega$ grid the outermost and the sparsest.
    - *Distributions*

2. **Solve the bank's value function.** Begin with a guess of the lending

1. **CR binds solution:** If the capital requirement binds, then we know $d' = (1-\chi)\ell(r;\omega)$. Then we need only search over the possible outcomes for $r$ and $s$. Moreover, we can rewrite problem (B.1) as

$$\begin{aligned} V(n,\omega,\overline{z},j) \quad = \quad & \max_{s,R} \psi\left(n + ((1-\chi)-c(s))\ell(R;\omega)\right) \\ & + R_f^{-1}\mathbb{E}_z\left[W\left(\ell(R;\omega)\left(\mathcal{R}(R,s;z)-R_d(1-\chi)\right),\omega,\frac{j\overline{z}+z}{j+1},j+1\right) \mid \overline{z},j\right] \end{aligned} \tag{B.12}$$

Then, the optimality condition for rate setting (analog of (B.5)) becomes

$$c(s) = \mathbb{E}_z\left[R_f^{-1}\frac{W_n'(z)}{\psi'(e)}\left(\left(1+\frac{\epsilon_{\mathcal{R},R}(z)}{\epsilon_{\ell,R}}\right)\mathcal{R}(R,s;z)-R_d(1-\chi)\right)\right] \tag{B.13}$$

while the optimality condition for screening is unchanged from (B.6). Since $\frac{\partial \ell}{\partial s} = 0$ by assumption, then, the candidate choice of $R$ entirely pins down the deposit policy. All that remains is to choose $s$: higher $s$ increases $R'$ state by state, but also lowers $e$ by raising the cost per unit of lending. Find the optimum by solving (B.6).

2. **CR slack solution:** If the capital requirement does not bind, then we know that $e = n+d'-c(s)\ell(R;\omega) \geq 0$ and $d' < (1-\chi)\ell(R;\omega)$. So for every $R$, the capital requirement places an upper bound on $d'$, $d_{\max}(R;\omega) = (1-\chi)\ell(R;\omega)$. Likewise, for every $R$ and $s$, the restriction that dividends be non-negative places a lower bound on $d'$, $d_{\min}(R,s;n,\omega) = c(s)\ell(R;\omega) - n$.

   For a candidate $R$ to be a viable solution, we must have that:

   (a) the implied level of deposits for the lowest allowable dividend ($e = 0$), which we define as $d'_{e=0}(R,s;n,\omega)$ must be positive; that is,

   $$d'_{e=0}(R,s;n,\omega) \equiv c(s)\ell(R;\omega) - n \geq 0 \tag{B.14}$$

   which can only occur when $c(s) \geq \frac{n}{\ell(R;\omega)}$, which places a lower bound on $s$:

   $$\tilde{s}_{\min}(R;n,\omega) = \frac{\frac{n}{\ell(R;\omega)} - 1}{\bar{c}} \tag{B.15}$$

   Since $s \geq 0$, we can define the effective lower bound on $s$ as $s_{\min}(R;\omega) \equiv \max\{0, \tilde{s}_{\min}(R;\omega)\}$.

   (b) the interval $[d_{\min}(R,s;n,\omega), d_{\max}(R,s;n,\omega)]$ must be non-empty, which implies that $c(s) - (1-\chi) \leq \frac{n}{\ell(R;\omega)}$. Under the assumption of a linear screening cost function in (30), this implies that we must have

   $$s \leq s_{\max}(R;n,\omega) \equiv \frac{\frac{n}{\ell(R;\omega)} - \chi}{\bar{c}} \tag{B.16}$$

   For this $R$ to be feasible, then, we must have $s_{\max} \geq 0$, i.e. $n \geq \chi\ell(R;\omega)$, which under functional form assumption (**??**) places the following lower bound on $R$

   $$R \geq R_{\min}(n,\omega) \equiv R_f \left(\frac{\chi\omega}{n}\right)^{\frac{1}{\phi}} \tag{B.17}$$

   The search range $[s_{\min}(R;\omega), s_{\max}(R;n,\omega)]$ must be non-empty, and $s_{\max} > s_{\min}$ as long as $\chi < 1$. Finally, having the capital requirement be slack is only viable if $R_{\min}(n,\omega) \leq \gamma$, the participation constraint of the borrower. This is the case if

   $$n \geq \chi \underbrace{\omega \left(\frac{\gamma}{R_f}\right)^{-\phi}}_{\underline{\ell}(\omega)} \tag{B.18}$$

   where $\underline{\ell}(\omega)$ is the lowest possible loan demand the bank can face while still issuing positive loans.

Combining pieces (a) and (b), to solve for the optimal policy conditional on the capital requirement being slack and such a policy being feasible based on the analysis above, we search for rates in the range $[R_{\min}(n,\omega), \gamma]$ in the outer loop, screening in the range

$[s_{\min}(R;\omega), s_{\max}(R;n,\omega)]$ in the middle loop, and deposits in the range $[d'_{\min}(R,s;n,\omega), d'_{\max}(R;\omega))$ in the inner loop.

So we can use the following algorithm. First, solve for the optimal policy assuming the capital requirement binds. Then, check condition (B.18): if it is violated, then the optimal policy coincides with the binding capital requirement policy; otherwise, solve for the optimal policy with the slack capital requirement and compare the values under binding and slack.

## B.6 Moments

**Aggregates** The bank share of total debt is equal to $\frac{L_b}{L_b+L_n}$. (Note that this is not exactly equal to $\frac{L_b}{L}$ given the CES aggregator which defines $L$.)

**Default and chargeoff rates** In the model, only bad types default, so the default rate at the bank level is equal to the share of bad types in the bank's pool of approved loans: $1-\rho(z;s)$. So the aggregate (average) default rate is $\int\int(1-\rho(z;g_s(x)))\mathrm{d}F(z;x)\mathrm{d}m(x)$. The chargeoff rate at the bank level is the ratio of total dollars lost, $\lambda(1-\rho(s;z))\mathcal{L}(z;r,s,x)$, to total dollars lent, $\mathcal{L}(z;r,s,x)$, and so the aggregate (average) chargeoff rate is simply $\lambda$ times the average default rate.