Bank Economic Capital*

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Abstract

Conventional measures of bank solvency fail to account for liquidity risks posed by deposits. Using public regulatory data, we develop *economic capital*, a framework that jointly quantifies credit, liquidity, and market risk. Economic capital identifies banks that fail years in advance, including those in March 2023, while book capital deteriorates just before failure. Predictive power comes from valuing liabilities, which are elevated long before asset impairment. The framework informs assessments of stabilization policies, credit provision, and financial stability — for example, following the Global Financial Crisis low rates depressed economic capital even as interest rate and liquidity risks grew.

Keywords: financial stability, bank capital, liquidity, solvency, deposits, bank credit
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1 Introduction

Banking sector distress is a key contributor to the length and severity of business cycles through its impact on credit provision (e.g., Bernanke, 2023), making bank solvency assessment central to financial monitoring and regulation. Yet, the most prevalent measures of bank health — capital metrics grounded in accounting rules — assume banks remain "going concerns," effectively treating the timing of payments as irrelevant to solvency. As a consequence, standard measures of capital fail to incorporate the inherent fragility posed by maturity transformation and demandable deposits. This disconnect between theory and measurement can obscure vulnerabilities, preventing a unified assessment of the interconnected risks banks face and obscuring their true economic leverage.

Since Modigliani and Miller (1958), economists have recognized that a firm's true leverage depends on the market value of its liabilities, not their book value (Myers, 1977), and this gap affects real economic determinants like investment (Myers and Majluf, 1984). However, three features make this distinction especially material for banks. First, banks are far more highly leveraged relative to typical firms, consequently, modest changes in liability values translate to large changes in economic capital. Second, the economic value of bank liabilities, specifically demand deposits, can meaningfully deviate from book values due to below-market rates and long effective maturity (e.g., Samuelson, 1945; Drechsler et al., 2021). In contrast, corporate debt typically trades near par absent distress. Third, bank liability values are uniquely fragile — runs force banks to sell assets or replace deposits at market rates, creating an alternative equilibrium where perceived insolvency can become actual insolvency (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005).

We bridge the significant disconnect between theory and practice by developing economic capital (EC), which calculates bank solvency as the present value of assets net of liabilities. Unlike book capital, EC reflects the market solvency of a bank by incorporating the timing of expected cash flows, the time value of money, and depositors' behavior. The framework jointly quantifies credit, interest rate, and funding liquidity risks that conventional approaches evaluate separately, preventing direct comparison across risk types. By valuing both sides of the balance sheet, EC captures the interaction between solvency and liquidity that theory emphasizes but standard measures omit. Critically, EC can be sensitized to depositor behavior. Under normal business conditions, we calculate EC; under funding stress, we calculate run economic capital (R-EC), which assumes uninsured deposits withdraw and are replaced at market rates. By accelerating the timing of liability payments, R-EC captures whether banks have sufficient asset value to satisfy creditors. Banks with adequate R-EC remain viable through funding stress; those with low R-EC are vulnerable to runs.

We validate that our measures provide a superior assessment of solvency by estimating their ability to predict bank failure. At up to a four-year horizon, we find EC and R-EC are statistically superior at predicting bank failure across a range of economic conditions. The superior predictive power comes primarily from liability valuation: banks approaching failure exhibit elevated liability values years before asset impairment emerges. The major banks that failed in March 2023 appear undercapitalized by R-EC as early as 2018, while alternative capital ratios remained relatively healthy even as the banks approached collapse. Moreover, when we combine their low levels of R-EC with our derived measure of interest rate risk in 2020, the banks that eventually failed appear uniquely insolvent relative to their peers. Of note, simply marking assets to market without valuing liabilities does not improve prediction, underscoring that liability valuation is essential.

Having validated the informativeness of our measures, we assess the evolution of banking sector solvency over time and find that economic capital tells a richer story than conventional measures. Following the Global Financial Crisis (GFC), book capital ratios recovered quickly and remained elevated through 2020. However, economic capital suggests this rapid improvement was illusory. EC recovered more slowly due to low long-term interest rates elevating deposit values. Moreover, as EC gradually improved, banks simultaneously accumulated exposure to run prone deposits, interest rate increases, and credit spreads. By the early 2020s, the combination of modest economic capital and elevated vulnerabilities created fragility that conventional measures failed to detect, demonstrating how our unified framework reveals systemic risks that might otherwise be neglected.

Beyond assessing financial stability, the framework enables several applications for both researchers and policymakers. Economic capital informs research on credit provision: we demonstrate that EC predicts loan growth at multi-year horizons, capturing potential constraints on lending that accounting-based capital misses. It also enables evaluation of policy interventions. As an example of the kind analysis that can be done, we examine the impact of the Bank Term Funding Program on R-EC and find only a modest benefit for the banks most at risk of failure, those with low levels of economic capital. More broadly, EC can be stressed to various scenarios such as interest rate shocks, credit losses, and funding runs, making it a versatile tool for researchers analyzing bank behavior and policymakers evaluating micro- and macro-prudential policies.

A central contribution of our work is demonstrating that comprehensive economic capital measures can be constructed using publicly available data. The substantial gap between reported book values and present values has long posed a measurement challenge, reflecting the complexity of valuing instruments like loans and deposits that are not actively traded and whose value depends on counterparty behavior. We address this challenge by developing transparent methods that leverage publicly available Call Report data for U.S. commercial banks from 1997 to 2025, enabling replication and extension.

The three estimated categories are (i) the value of portfolios with fixed rate instruments, (ii) the value of demand deposits, and (iii) the value of necessary operating expenses. For fixed-rate portfolios (loans, time deposits, and long-term debt), we estimate present values using reported maturity schedules combined with bank-specific, time-varying credit spreads and prepayment behavior. This duration-based approach captures how discount rates affect specific maturities while also accounting for the material convexity in mortgage portfolios (Hanson, 2014) and the sensitivity of loan values to aggregate risk premia.

For demand deposits, we take a discounted value approach that estimates value as a function of interest rate sensitivity (i.e., deposit beta) conditional on a common drawdown rate (i.e., effective maturity). We depart from standard practice that relies on near-term or constant betas. Instead, we estimate forward-looking, bank-specific deposit betas using hedonic regressions over historical tightening cycles. This captures material variation in deposit values both across banks and over time as determined by the expected path of rates and bank's deposit characteristics.

For operating expenses, we estimate the minimal costs necessary for banks to maintain going-concern operations using hedonic regressions that allow expenses to vary with bank business models. Our notion of necessary expenses excludes revenues not reflected in our present value calculations (like fee-based franchises or excess loan returns).

We exclude several components of bank value from our calculations, primarily off-balance sheet assets and liabilities. First, with respect to noninterest income such as fee-based franchises, we exclude both the income and associated expense. Given our objective is to measure bank solvency, we conservatively assume that a distressed or near-insolvent bank cannot raise funds based on these future cash flows. Second, we do not account for derivatives that might hedge banks against changes in market prices, as publicly available data is insufficient to assess the state-contingent value of hedges. Research suggests hedges are not a significant source of value for the vast majority of banks (McPhail et al., 2023; Granja et al., 2024), although we highlight this as an area where information collection could be improved. Third, we do not include the potential impact of off-balance sheet commitments like credit lines, whose behavior is highly heterogeneous across borrower types (Chodorow-Reich et al., 2022) with impacts for both assets and liabilities (Kashyap et al., 2002).

Our core contribution is providing a transparent framework for measuring bank solvency that aligns banking theory's emphasis on funding fragility with accounting-based measurement. As a novel solvency measure spanning nearly three decades, economic capital enables investigation of fundamental questions about bank credit provision, monetary policy transmission, and financial stability interventions. Our estimates are not without a few caveats. We lack granular details on loans, deposits, expenses, and hedges. However, our assumptions can be readily sensitized and, with sufficient data, any asset or liability can be incorporated into our approach. Finally, our measure applies to commercial banks rather than consolidated bank holding companies, so we do not capture activities in non-bank subsidiaries such as broker-dealers.

Our valuation of bank liabilities builds on a long research tradition examining the special properties of deposits for bank value. Samuelson (1945) first recognized that deposits provide banks with economic rents through below-market rates. Flannery and James (1984) provided early empirical evidence on the long effective maturity of deposits. Hutchison and Pennacchi (1996) developed methods to measure the gap between book and economic values. More recently, Drechsler et al. (2017) demonstrates how deposit franchise values can interact with monetary policy to affect intermediation activity. Empirical work has documented substantial variation in deposit betas (Emin et al., 2023) and cross-sectional deposit value (Egan et al., 2021). We build on these insights by incorporating our own approach that results in time-varying, bank-specific deposit values that play a significant role in our assessments of solvency.

In related work, the literature debates whether deposits are an effective hedge to interest rate risk in bank assets — a question tangential to our combined asset-liability valuation framework. Some work finds deposits provide natural hedges (Flannery and James, 1984; Drechsler et al., 2021), while others conclude hedges are limited without specific maturity or cost assumptions (DeMarzo et al., 2024). Evidence is mixed depending on methods. English et al. (2018) finds that rate increases can reduce bank equity value and Begenau et al. (2015) emphasize that IRR exposure has varied over time. We contribute to this debate by relating interest rate risk to a comparable measure of solvency. Critically, we find that interest rate exposure is heterogeneous and dynamic – the sign and magnitude vary with the expected path of rates, asset composition, and depositor characteristics. Our estimates of asset and liability values reveal substantial nuance to the question of whether banks are hedged to interest rates.

Several recent papers apply these insights to banking stress during the 2022-2023 interest rate cycle. Some focus primarily on asset-side effects: Flannery and Sorescu (2023) show that marking loans and securities to market would have caused about half of banks to fail regulatory requirements. Others combine asset losses with deposit stability, generating equilibria where depositors run when concerned about market solvency (Drechsler et al., 2023; Haddad et al., 2023; Jiang et al., 2024; Luck et al., 2023). These papers also emphasize uninsured deposits as the key indicator of run risk and propose capital measures that assume uninsured deposits run (e.g., Jiang et al., 2024; Curti and Gerlach, 2024). Our contribution is to value all assets and liabilities — including insured deposits — over a long time period spanning multiple business cycles. Rather than modifying regulatory capital measures, our approach recovers a dynamic economic measure of market solvency. We show that comprehensively valuing assets and liabilities improves failure prediction outside the 2023 episode, revealing that economic capital is broadly applicable to assessing banking sector stability.

The rest of this paper is organized as follows. Section 2 provides additional detail on existing approaches to measuring bank risk. Section 3 outlines the data and methods we use to calculate present values. Section 4 tests economic capital as a predictor of bank health, before illustrating applications to banking policy and research. Section 5 summarizes our findings.

2 Measures of Solvency

Bank stakeholders use a wide range of measures to assess the solvency of individual banks and the capital strength of the banking industry. These measures differ in how they recognize changes in the value of bank assets, liabilities, and off-balance sheet positions due to credit deterioration, interest rate movements, and other market factors. These inconsistencies complicate interpretation and obscure economic solvency.

The most widely used measures of solvency are regulatory capital ratios and tangible common equity (TCE), which in the United States embed definitions of bank equity based on generally accepted accounting principles (GAAP). Under U.S. GAAP, many assets and liabilities on banks' balance sheets are carried at amortized cost rather than at fair market values. Credit impairment is recognized through loan loss allowances, but changes in value from interest rate and spread movements are generally ignored except for trading and available-for-sale (AFS) positions. On the liability side of the balance sheet, value changes are rarely recognized. Consequently, reported values of capital embed a mixture of fair values, par values, and amortized costs from both sides of the balance sheet.

Given this approach, these capital ratios may not be accurate assessments of banks' solvency, especially if a bank has significant mismatch between the duration of its assets and liabilities. While comfortably operating as a going-concern, differences between book capital and EC might not be particularly important; however, during times of stress, creditors are sensitive to economic solvency rather than book capital. Thus, it is important to have solvency measures that do not depend solely on accounting and regulatory constructs to identify weak banks.

To address these gaps, practitioners have developed alternatives to conventional capital ratios. These alternatives fall into two broad categories: point-in-time measures that summarize current bank capital given prevailing conditions, and stress measures that estimate capital under adverse scenarios (discussed below). The simplest point-in-time alternatives incorporate mark-to-market (MTM) changes in bank assets. These measures typically include market gains and losses on securities, but more sophisticated approaches also recognize changes in the value of loans (Flannery and Sorescu, 2023; Jiang et al., 2024). Industry analysts often refer to such measures as market-adjusted TCE (e.g., S&P Global, 2023).

However, these measures fail to distinguish banks with different liability structures as they ignore liability valuation, presenting an incomplete picture of solvency. This omission is particularly problematic for deposits, which carry below-market rates (Hannan and Berger, 1991) with uncertain effective maturity, creating substantial gaps between book and economic values that can widen when deposit rates lag market rates (e.g., Drechsler et al., 2017). A bank heavily reliant on uninsured deposits faces fundamentally different fragility than one funded with insured deposits, yet asset-only measures treat them identically.

Recognizing liabilities', and especially deposits', potential to hedge interest rate risk, supervisors developed Economic Value of Equity (EVE) to evaluate banks' net exposure to interest rate risk (Basel Committee on Banking Supervision, 2015). EVE is nearly always used to assess potential *changes* in economic value rather than the *level* of value. Moreover, changes in EVE are typically compared to regulatory or book capital rather than to the level of EVE itself, which leads to biased assessments. For instance, comparing EVE changes to regulatory capital fails to distinguish banks where economic capital exceeds regulatory requirements from those where it falls short — a critical distinction for assessing true risk exposure.

Other measures that speak to the risk of *changes* in bank solvency include Earnings-at-Risk (EaR) and stress testing. EaR estimates how interest rate changes affect earnings over a short horizon, typically one year, ignoring longer-term effects. This short horizon can create perverse incentives to shift risk beyond the measurement window. Stress testing also assesses the risk to near-term earnings using broad, macroeconomic scenarios. In stress testing, the impact to net income under these scenarios is translated into changes in regulatory capital over a nine-quarter horizon. Thus, the current stress testing regime inherits the limitations of accounting-based regulatory capital measures. Both EaR and stress testing are myopic, missing longer-dated solvency effects

Economic capital provides an internally consistent framework for both point-in-time measurement and stress scenario analysis. Unlike measures that separate interest rate risk, credit risk, and funding risk into incomparable metrics, our framework jointly quantifies all three in a common unit. Using long-standing regulatory report data, we construct historical estimates spanning several previous interest rate cycles. This enables both us to evaluate economic capital as a point-in-time assessment of solvency, to provide a retrospective analysis of the evolution of banking sector risk and to conduct forward-looking stress analysis by varying depositor behavior, interest rates, and credit spreads.

3 Data and Methods

This section outlines our approach to measuring solvency. For brevity, we have focused on key inputs, the conceptual approach and important limitations. The Internet Appendix (IA) to this paper contains a detailed description and robustness analyses.

Our proposed measure of bank solvency, EC, is derived from the present value of assets net of the present value of liabilities. EC can be written as the sum of cash flows from assets, A, and liabilities, L, slotted into time-to-maturity buckets $t \in 1, 2, 3..., T$.

$$\begin{aligned} \text{EC} &= \sum_{t=1}^{T} \frac{A_t}{(1 + rf_t + rp_t)^t} - \sum_{t=1}^{T} \frac{L_t}{(1 + rf_t)^t} \\ &= PV_{Assets} - PV_{Liabilities} \end{aligned} \tag{1}$$

Assets are evaluated using the risk-free rate, rf_t, plus an appropriate risk premium, rp_t, whereas liabilities are discounted using risk-free rates. The choice of rates is intended to recover the assets available to satisfy creditors. The asset discount rate approximates the market value of assets, which is relevant in the event the bank must sell or borrow against them. The liability discount rate assumes liabilities are repaid in full, hence the prospect of default does not create value for the bank. Implicit in this approach is that upon maturity assets and liabilities are replaced in a competitive market place at prevailing market rates.

We include the present value of certain operating expenses as a liability to capture the costs necessary to realize the value of assets and liabilities. We do not include the value of other off-balance sheet franchises, like fee-based businesses such as asset management. We take a conservative approach and assume the present value of these businesses is not relevant to creditors, particularly near default. Along these lines, we also exclude intangible assets from our calculations.

EC is conceptually akin to the EVE measures that recognize the hedging benefits of deposits to recover exposure to interest rate risk. However, we depart from EVE in two important ways. First, we design our calculations to recover solvency; hence, we focus on the level using discount rates that imply a buffer to creditor losses. Second, we consider sensitivities related to a broader set of financial conditions that just interest rates.

3.1 Data

Our primary data source is the Call Report (FFIEC 031/041), which is filed by commercial banks. The Call Report contains balance sheet and income statement information, along with a range of supplementary schedules with critical details about the maturity composition of assets and liabilities.

Call Reports are filed quarterly by every U.S. commercial bank and some other U.S. depository institutions. These reports are available for a comparatively long historical period, dating back to 1959, but our sample period starts in 1997:Q2, as this is the first date when key supplementary schedules were filed. Our sample contains all banks that filed Call Reports at any point between 1997:Q2 and 2025:Q1, with some exclusions. Specifically, we exclude banks with less than \$50m in assets or banks with atypical business models.[1] Our final sample includes 11,619 unique institutions that represent over 85% of industry assets during the sample period.

The most direct method for recovering the present value of a financial instrument (asset or liability) is to use values reported on the Call Report. Some assets are reported at fair value (i.e., market value) on the balance sheet while some other items' fair values are reported in supplementary schedules. In both cases, we assume the reported fair value reflects the funds available if the item is sold or borrowed against. For most short maturity or floating rate items, we take the reported book value as the present value. The exception is demand deposits, which we value assuming a longer effective maturity. The remaining assets and liabilities are only reported on an amortized cost basis.[2]

For balance sheet categories that include fixed-rate instruments, we exploit the maturity data available in supplementary schedules of the Call Report that allow us to estimate the present value. The schedules group instruments into categories by remaining maturity or next repricing date, thereby allocating floating rate instruments to near-term maturities. These schedules are available for residential real estate (RRE) loans, non-RRE (all other)

[1]The asset cut-off of \$50m is indexed to 2023 dollars using the GDP price deflator and excludes $\sim 10\%$ of bank-quarter observations. We exclude Call Report filers that are designated as domestic branches, domestic entity other, foreign bank, foreign banking organization, and non-deposit trust companies. These entities represent less than 1% of filers. We also exclude banks that are designated as custodian banks (e.g., trusts) as deposits for these banks have unique deposit insurance and depositor behavior. These business model exclusions remove $< 1\%$ of bank-quarter observations.

[2]Amortized cost records the value based on the original cost of the item at purchase, but adjusts this cost for principal repayments and the amortization of any premium/discount paid relative to the face value of the instrument.

loans, time deposits, subordinated debt, and other borrowing, beginning in 1997. The details for this procedure are discussed in Section 3.2. For demand deposits, which are quasi-fixed rate with no explicit maturity, we use data from the Call Report and the FDIC Summary of Deposits (SoD) to estimate the relevant parameters necessary to calculate the present value. Our approach to demand deposit valuation is outlined in Section 3.3.

Table 1 summarizes the composition of bank balance sheets by the source of present value in our calculations. Current regulatory reports provide very little insight about the present value of several significant balance sheet components. Roughly 35% of assets are reported at par or fair value. But, we must estimate values for the largest category, held-for-investment (HFI) loans, which makes up around 60% of bank assets. On the liability side, the vast majority of categories must be estimated, including demand deposits, which are roughly 50% of book assets. The magnitudes of the estimated components underscore the opacity of bank solvency using conventional reporting standards.

In addition to incorporating balance sheet items, we calculate the value of the expenses necessary to operate the bank and provide services to depositors. This off-balance sheet liability is estimated using Call Report and SoD data. The methodology is described in Section 3.4.

We utilize several data sources to form relevant discount rates. For risk-free rates at a range of maturities we rely on constant maturity Treasury par yields as described by Gürkaynak et al. (2007), henceforth GSW, and infer rates for each quarterly maturity horizon. For certain financial instruments, such as deposits, we use the risk-neutral yields derived from GSW by Adrian et al. (2013), or ACM. In addition to risk-free rates, we incorporate credit spreads to estimate risk premia using option-adjusted spreads implied by ICE Bank of America corporate bond indices which we map to specific maturities using the High Quality Market (HQM) corporate credit curve published by the U.S. Treasury.

The calculations in this paper could be adapted to consider bank holding companies, or BHCs, using the FR Y-9C report, which contains the consolidated financials of BHCs. However, the Y-9C lacks critical details on the maturity of assets/liabilities that are important for our calculations. In addition, non-bank subsidiaries in BHCs present additional modeling challenges such as large off-balance sheet exposures and significant noninterest income lines of business.

3.2 Portfolios with fixed-rate instruments

Banks hold and borrow using fixed-rate securities whose value is sensitive to shifts in discount rates. However, banks are not required to report the fair value of several categories of these

Table 1: Balance sheet composition. This table summarizes the composition of the bank balance sheets in our sample from 1997:Q2 through 2025:Q1. All items are scaled by book assets. Ratios are reported based on the sample mean and in aggregate (i.e., Industry). Assets and liabilities are categorized based on our approach to obtaining present values. *Fair Value* items are reported on balance sheets or in supplementary schedules (*Supplementary Report*) at par or fair value. *Amortized Cost* items are only reported at amortized cost and we either estimate them using the methodologies outlined in Sections 3.2 and 3.3, *Fixed-Rate Portfolios* or *Demand Deposits*; or, we use the reported book values, *Book Value Used*. *IB* refers to interest bearing and *NIB* to non-interest bearing. *AFS* is available for sale, *HFS* is held for sale, and *HFI* held for investment. Variable construction and data sources are further detailed in IA Section A.

(a) Assets

	% of Assets	
	Mean	**Industry**
Fair Value:		
IB balances	3.94	4.91
NIB balances	2.80	2.37
FF & Repo	2.61	3.71
AFS securities	18.83	15.98
Equity securities	0.20	0.17
HFS loans	0.43	1.48
Trading assets	0.04	4.51
Other	1.11	0.88
Supplementary Report:		
HTM securities	3.58	3.51
Mort. servicing rights	0.04	0.29
Amortized Cost:		
Book Value Used		
Fixed assets	1.77	1.03
Intangibles	0.42	1.99
Other	1.64	3.71
Fixed-Rate Portfolio:		
HFI Loans	63.50	56.41
Loan loss reserves	-0.92	-0.96

(b) Liabilities

	% of Assets	
	Mean	**Industry**
Fair Value:		
FF & Repo	1.33	4.88
Trading liabilities	0.01	2.13
Other	0.05	0.24
Amortized Cost:		
Book Value Used		
Other	0.69	2.16
Fixed-Rate Portfolio:		
Sub. debt	0.03	0.92
Other debt	3.76	7.16
Time deposits	34.22	16.76
Demand Deposits:		
Domestic	49.18	48.16
Foreign	0.08	7.43
Total	49.25	55.59

instruments. On the asset side of the balance sheet, we must estimate the present value of HFI loans. On the liability side, we must estimate values for three categories: subordinated debt, other borrowed money, and time deposits.[3]

Ideally, we would have granular information on the remaining maturity, origination date, coupon, and risk characteristics of the positions we are valuing, but this information is not available for the vast majority of banks. The Call Report does contain maturity schedules

[3]We treat time deposits as distinct from demand deposits, consistent with their typical pricing behavior. Time deposit rates track closely with prevailing interest rates as rates rise and, due to their maturity structure, tend to exceed prevailing rates when rates decline, Figure IA18. This treatment also reflects time deposits use as a marginal form of financing in tightening cycles (Kang-Landsberg et al., 2023).

for the relevant instruments that categorizes book values based on the minimum of the instrument's maturity or next repricing date. Floating rate obligations in these portfolios are reported in the shortest maturity category. Conditional on the available data, we develop a method that calculates changes in present value using estimated durations and changes in discount rates.

Based on the maturity schedules for each portfolio, we uniformly assign book values to time-to-maturity buckets, BV_t^m, for each quarter, t, and the range of time-to-maturity horizons, m. For example, mortgages with a maturity from 5 to 15 years are uniformly distributed to buckets with quarters-to-maturity, m, ranging from 21 through 60. For each bank, we derive the present value of positions using the following dynamic equation:

$$PV_t^m = O_t^m + PV_{t-1}^{m+1}(1 + \Delta y_t^{m+1} D_{t-1}^{m+1} pp_t^m). \tag{2}$$

The present value, PV_t^m, is the sum of new originations, O_t^m, the prior present value, PV_{t-1}^{m+1}, and its change in value due to changes in discount rates. The prior present value that corresponds with PV_t^m is one quarter prior, $t-1$, and has one additional quarter-to-maturity, $m+1$. The change in the prior present value depends on the change in the discount rate, Δy_t^m, a prepayment factor, pp_t^m, the duration, D_{t-1}^m, and the prior present value, PV_{t-1}^{m+1}. We sum across time-to-maturity categories, m, at each point in time t to obtain the total present value of a particular portfolio.[4] Our use of durations means that we may overstate the impact of a large changes in rates, particularly for portfolios with material convexity. The remainder of this section outlines how we obtain the necessary parameters. Details and supporting analysis is contained in IA Section B.

Initial Value (PV_0): To iterate on Equation 2, we require an initial present value, PV_0^m, for each maturity bucket. To generate these initial values, we assume that the book value equals the present value at specific points in time, $PV_0^m = BV_0^m$, and then model changes from these initial values per Equation 2. Book values and present values are roughly the same at origination when yields and discount rates are equal. To select these initial quarters, $t = 0$, we identify dates that reflect inflection points in the interest rate cycle when rates begin to rise relative to the recent past and when many loans have recently been refinanced.[5] The turning point dates we identify are: 1997:Q1, 1999:Q2, 2004:Q2, 2013:Q2, and 2021:Q4. Fair value data for securities and loans show that book and present values roughly equate

[4]We cap the present value of loans to book value at 1.2 for residential loans and 1.1 for all other loans. This impacts less than 1% of bank-quarter observations.

[5]This is the same assumption made in papers that calculate unrealized losses on loans and securities during the 2022 interest rate cycle, which set book and market values equal at the end of 2021. See, for instance (Flannery and Sorescu, 2023)

around these quarters (Figure IA6b and Table IA7).

Originations & Prepayment (O_t^m, pp_t): Portfolios evolve over time – instruments approach maturity, borrowers pre-pay loans, and new instruments are originated. New originations for each time-to-maturity bucket are estimated by comparing a projected book value to the current book value. Projected book values are constructed by rolling-forward the book value of a one-quarter higher maturity bucket in the prior quarter and reducing it by industry prepayment rates. If the book value for a bucket is higher than its projection, we assume the incremental value is new originations. If the book value is lower than the projection, we assume prepayment for that bucket is in excess of the industry rate.

Prepayment benefits borrowers relative to lenders as borrowers are likely to prepay when prevailing rates are lower than that of the loan which limits valuation gains. For residential mortgages, we estimate industry-level prepayment rates using the NY Fed/Equifax Consumer Credit Panel; for all other loans, we assume a continuum of prepayments from 5% per annum up to 25% per annum based on the relative level of interest rates to historical averages.[6] We assume banks cannot prepay liabilities which is conservative with respect to solvency and consistent with a distressed bank facing refinancing constraints.

Duration (D_t^m): Given data limitations, we cannot calculate the precise duration. However, we can approximate duration using several assumptions. The duration, D^m, of a coupon bond that pays f times a year and is trading where the coupon rate matches the yield is given by the scaled derivative of the price, p relative to the yield, y,

$$D = \frac{\partial p}{\partial y}\frac{1}{p} = \frac{1}{py}\left[1 - \frac{1}{(1+y/f)^{fm}}\right], \tag{3}$$

where the time-to-maturity in years is denoted by m. We calculate the duration quarterly for each maturity category using relevant rates.[7] For loans, we use a variation on Equation 3 that incorporates expected prepayment rates that lower contractual durations, see IA Section B.5.

Discount rates, y_t^m: Discount rates inform both duration, Eq. 3, and the evolution of present value, Eq. 2. The ideal discount rate reflects the opportunity cost of an instrument

[6]Other loans contain a variety of loan types including consumer loans, CRE, and C&I. These groups tend to have a wide-range of pre-payment behavior depending on the type of borrower and the use of prepayment penalties by lenders. While further refinements could be made to this assumption, the impact is modest given the average contractual maturity of these loans and conservative given that loans that exceed book value are more likely to prepay.

[7]To assign fair market value using duration, we use the par-value duration, $p = 1$, and semi-annual coupons, $f = 2$.

with respect to maturity and risk. For loans, we construct a *heterogeneous* (bank-specific, time-varying) discount rate that combines a risk-free rate and a risk premium which reflects bank-specific portfolio risk. Both rate components vary with maturity and time to capture changes in the yield curve and the term structure of credit risk (e.g., van Binsbergen and Koijen, 2017).

For each maturity bucket, we use a risk-free rate consistent with the corresponding constant-maturity par yield. To incorporate the risk premium, we assume that higher loan rates reflect riskier loans and assign credit spreads accordingly. Specifically, we calculate the difference between each bank's interest rate on loans relative to AA corporate yields with a similar maturity composition. We then use these differences as a measure of relative portfolio risk and assign a corporate credit rating from AA up to the average of single-B and BB (BB-B).[8] Finally, we use these ratings to assign risk premia to specific maturities using the HQM corporate credit curve.

For liabilities, we discount using risk-free or near-risk-free rates. For subordinated debt, we use constant-maturity par yields plus the AAA credit spread. For other borrowing and time deposits, we use ACM risk-neutral rates which do not include a term premium or liquidity discount. The lack of term premium is reasonable for these rates as they are primarily short term while the lack of a liquidity discount ensures bank funding costs do not benefit from the convenience yields that can depress Treasuries (Fleckenstein and Longstaff, 2024).[9]

Credit losses: We reduce loan present values by the proportion of loans that have been reserved against. While this may partialy double-count default risk captured in discount rats, our approach is conservative from a solvency perspective given that loan loss reserves typically lag expected defaults. The adoption of forward-looking, Current Expected Credit Loss (CECL) standards in 2020 may have improved responsiveness to economic conditions; however, properly accounting for the impact of this change requires further research on its real-world impact.

3.2.1 Estimated present values for fixed-rate instruments

Figure 1 plots the distribution of present value to book value for the fixed-rate asset and liability portfolios. Figure 1a depicts the distribution of loan portfolio valuations, where we show these values as a ratio to their reported book values gross of loan loss reserves. The two

[8]We use corporate spreads for all loan types due to data availability. But this approach could be modified to consider spreads for specific loan types.

[9]This is particularly important during extreme conditions in the market (e.g., COVID, GFC) when GSW yields are extremely low but do not represent a viable funding opportunity for banks.

prominent declines in loan values occur during the GFC and the recent rate hike cycle that began in 2022. Both shocks are typified by higher yields, as indicated by the BB-B yield; however, during the GFC this is due to higher credit spreads and in 2022 higher risk-free yields. In both episodes, average loan portfolio present values fall to 90 percent of reported book values.

Loan present values are on average below those of book values, in part because of loan loss reserves reducing the value of the loan relative to its gross value, but also due to a key valuation assumption. We assume that the discount and coupon rates are equal which effectively rules out excess returns on loans. If banks are able to earn interest on loans that exceed their risk (Schwert, 2020), then we undervalue loan portfolios. This approach is conservative with respect to capital and more closely reflects the financeable value of loans when investors are concerned about banks' survival. We take this conservatism into account when we consider the operating expenses of the bank by excluding the costs of lending from our estimates of necessary expenses.

Despite a similar methodology, the patterns are substantially different for fixed-rate liabilities, Figure 1b. Relative to loans, fixed liabilities do not include prepayment or loan loss reserves which allows them to exceed book values when rates fall. The liability values are also not exposed to risk premia, meaning that heterogeneity in risk and time-variation in credit spreads do not impact fixed-rate liability values. As a result, fixed-rate liabilities cannot hedge against changes in loan values that result from shifts in the risk premium.

3.3 Demand deposits

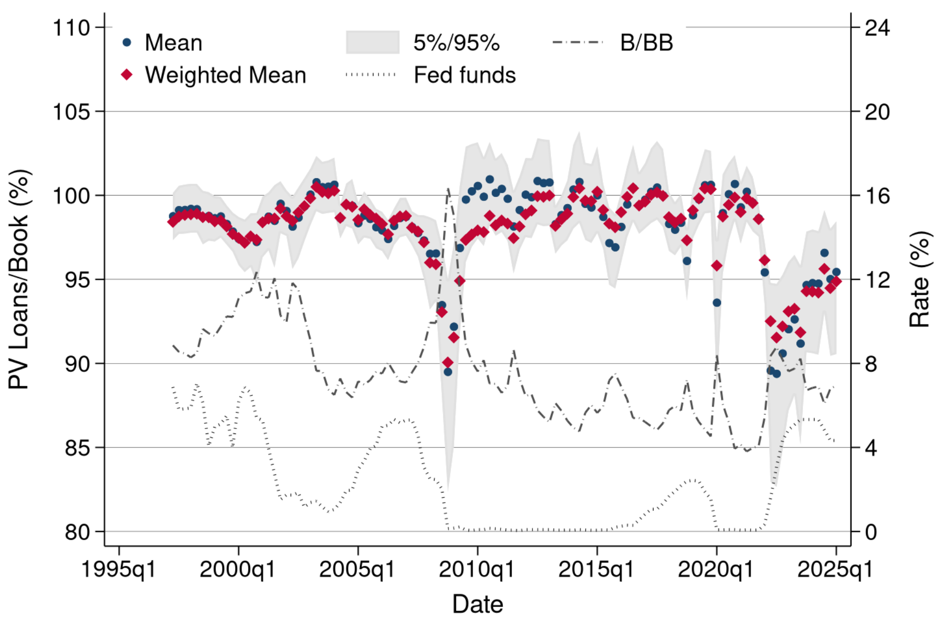
Demandable debt introduces unique valuation challenges as the quantity and cost of the debt is a function of lender and borrower behavior rather than explicit contractual terms. As noted in Table 1, demand deposits are the primary source of funding for the banking sector, so their treatment is critical to assessing bank value. As with our method for the fixed rate portfolio, our objective is to develop a robust methodology using available information that captures cross-sectional and time-varying differences in deposit values. In addition to estimating a benchmark value of deposits that reflects normal operating conditions, we also want to be able to explore the alternative equilibrium inherent in demandable debt by calculating a stress valuation.

We model demand deposits, both non-interest-bearing (NIB) and interest-bearing (IB), as a single category to account for shifts in product mix as interest rates change.[10] Hence, variation in implied demand deposit rates implicitly captures migration from NIB accounts

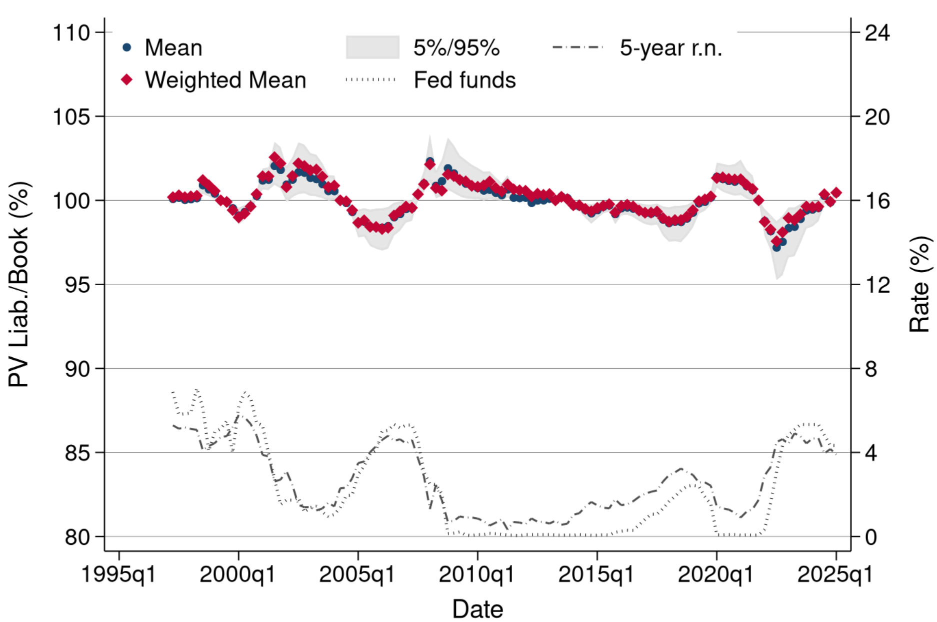
[10]Deposit mix shifts toward NIB deposits when rates are low and toward IB deposits (e.g., savings accounts, MMDAs) at higher rates, particularly for larger banks. See Figure IA17.

Figure 1. Distribution of fixed-rate portfolio values over time. This figure plots the implied distribution of the present value to book values for fixed-rate assets and liability instruments from 1997:Q2 to present using the methodology outlined in Section 3.2. Figure 1a plots the present value of loans relative to the book value of loans gross of reserves and includes the average of the BB and single-B yield as well as the fed funds rate. Figure 1b plots the present value of subordinated debt, other borrowing, and time deposits relative to their book value and includes the 5-year risk neutral yield and the fed funds rate. The chart includes the 5th-95th percentile range, the average and the weighted average.

(a) PV Loans/Book



(b) PV FR Liab./Book



to IB accounts. We value domestic and foreign demand deposits separately given they are not easily substituted by depositors and they display unique pricing behavior, but we rely on the same conceptual approach for each.

We calculate the present value of demand deposits as the function of financial terms: interest paid and effective maturity (i.e., drawdowns). We incorporate the cost of providing deposit-related services in Section 3.4. Our benchmark approach treats deposits as long-dated with stable maturity; a perpetuity with drawdowns formulation provides a parsimonious representation of our valuation approach and the key parameters. For bank i at time t the present value of demand deposits is,

$$PV_{i,t}^{D} = \left[\frac{\beta_{i,t} y_t^D + \delta}{y_t^D + \delta}\right] BV_{i,t}^{D} \tag{4}$$

where $\beta_{i,t}$ in this formulation is the ratio of deposit expense to the discount rate, y_t^D is the discount rate on deposits, and δ the annual withdrawal rate of deposits.[11] Multiplying the valuation factor by the amount of deposits (e.g., the book value), $BV_{i,t}^{D}$, provides the present value.

The present value of deposits increases with deposit expenses and drawdowns (β and δ). As either rise, a bank must fund itself at the discount rate rather than lower, quasi-fixed rates typically paid on demand deposits.[12] To parsimoniously value deposits, we assume a common drawdown rate across banks and estimate bank-specific, time-varying betas. Hence, betas determine variation in deposit values in the cross-section and over time.

Discount rates, y_t^D: Deposit rates are typically compared to other short-term rates, such as the fed funds rate. However, the present value is a function of parameters over the effective maturity of the deposits. As with time deposits, we choose to discount deposits at risk-neutral yields. We choose these yields to eliminate the impact of risk factors that are more relevant to Treasuries than deposits, such as term premia and liquidity premia. Given our treatment of deposits as long-dated, we focus on a 5-year horizon as representative of long-term expectations.

Drawdowns, δ: In assessing interest rate risk, analysts and regulators generally assume a fixed maturity for deposits, typically in the range of 5 to 10 years regardless of pricing (e.g.,

[11] In practice, we incorporate the slope of the yield by valuing the first five years before applying the perpetuity.

[12] The valuation of interest and drawdowns in Eq. 4 converges to one when: $\beta = 1$ or $\delta = 1 + (1 - \beta)y$. This is consistent with prices and drawdowns both decreasing the "franchise value of deposits". The choice of drawdowns or beta has distinct implications for the modeling of costs which we address when we discuss funding shocks.

Office of the Comptroller of the Currency, 2024, Table 1d).[13] But these determinations lack clear empirical support. Absent distress, depository institutions typically retain a pricing advantage to prevailing risk-free rates. In addition, microdata on the maturity of demand deposit accounts supports relatively long effective maturities (Sherman, 2013).

Based on these factors, we select a universal drawdown rate of 5% per annum and calculate deposit betas for each bank consistent with this rate. We also consider a stressed funding approach that effectively shortens the maturity of uninsured deposits. By considering a long-maturity scenario as well as a funding risk scenario, we are able to capture the range of potential valuations.[14]

Deposit betas, $\beta_{i,t}$: For valuation, the critical parameter is the expected deposit beta, hence our estimation of deposit betas is designed to recover heterogeneity and time-variation in long-term betas conditional on our deposit growth assumption and the expected path of rates. To do so, we estimate a hedonic regression that explains future deposit betas as a function of bank characteristics, interest rates, and bank deposit growth. Using this empirical model, we predict betas for each bank-quarter that reflect heterogeneity in deposit bases and time-variation in the expected path of rates.

The regression estimates explains the terminal ratio of the deposit rate to the fed funds rate in five prior tightening cycles. Evidence shows deposit rates respond with a lag to interest rates (e.g., Diebold and Sharpe, 1990), particularly in a rising rate environment; hence, terminal ratios better capture the ultimate relation between deposit rates and interest rates.[15] We regress bank-specific betas for each hiking cycle on bank characteristics at the onset of the cycle and cycle-specific variables such bank-specific deposit growth, the length of the cycle and the ultimate level of rates. Using the coefficients generated from the model, we predict a panel of standardized, long-term deposit sensitivities for each bank-quarter conditional on current bank characteristics, our specified drawdown rate, an assumed cycle length of 12 quarters, and the current 5-year risk-neutral forward rate. [16]

[13] A typical argument is that shorter maturities are 'conservative' as they assume sooner repayment, but this can induce poor asset-liability management, conflate banks with different levels of deposit risk, and encourage the use of deposits with greater risk.

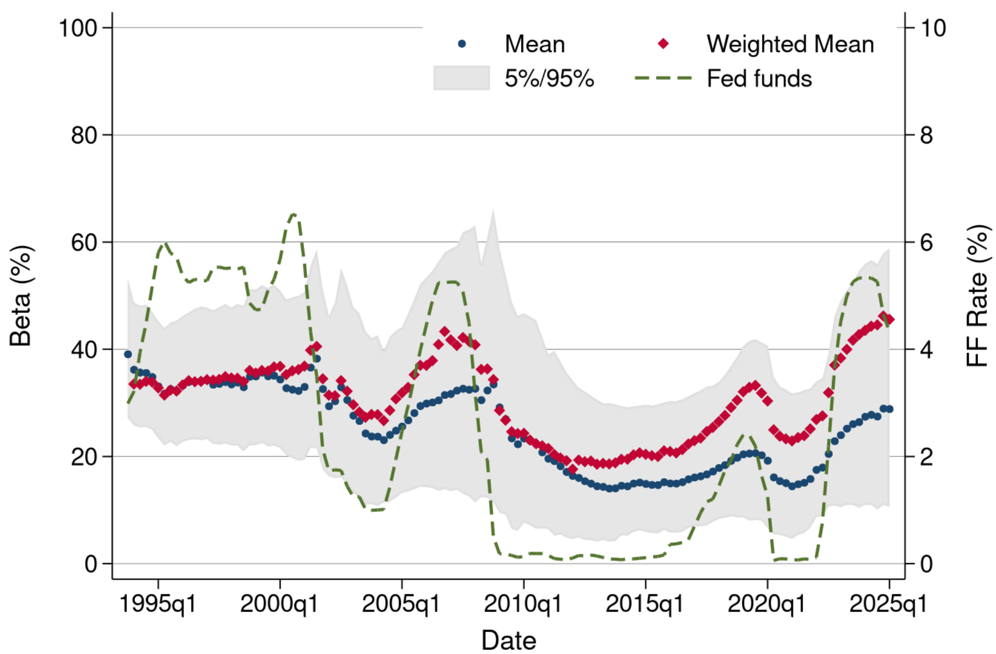
[14] We have also explored an even more extreme valuation approach that treats deposits as a perpetuity as suggested by DeMarzo et al. (2024). Such an approach reduces the present value of demand deposits, increasing EC. This is somewhat offset by a higher expense value, consistent with the cost of retaining and servicing deposits in perpetuity.

[15] The extant literature and supervisory practice have largely focused on using near-term relative changes to estimate deposit sensitivities. Near-term sensitivities deviate than those at longer horizons due to asynchronous changes between deposit rates and the fed funds rates and a non-linear relation with the level of rates (i.e., convexity; Greenwald et al. (2023)).

[16] Out-of-sample tests support the efficacy of these estimates. For the 2021-2024 cycle, predicted betas based on prior hiking cycles explain 80% of the cross-sectional variation with a slope coefficient of 1.12.

The resulting distribution of estimated long-term deposit betas across banks and over time is presented in Figure 2. The figure shows the 5th to 95th percentile range of estimated betas in each quarter of our sample period along with five-year risk neutral forward rate. The estimates capture two important features of deposit betas. First, there is a growing disparity across the size distribution of banks. This is evidenced by the growing gap between the weighted average (red triangles) and the unweighted average (blue dots) across banks. Second, long-term betas are positively related to long-term rates. Roughly 20 percent of the time-series variation in betas is explained by changes in the long-term discount rate, with the remainder related to changes in bank characteristics, such as the average size of deposit accounts.

Figure 2. Estimated long-term betas. This figure plots the distribution of long-term demand deposit betas predicted by Table IA13, Column (1), conditional on bank characteristics, a 5% drawdown rate, a cycle length of 12 quarters and the 5- to 10-year risk-neutral forward rate. Deposit betas are the ratio of the deposit rate to the fed funds rate.



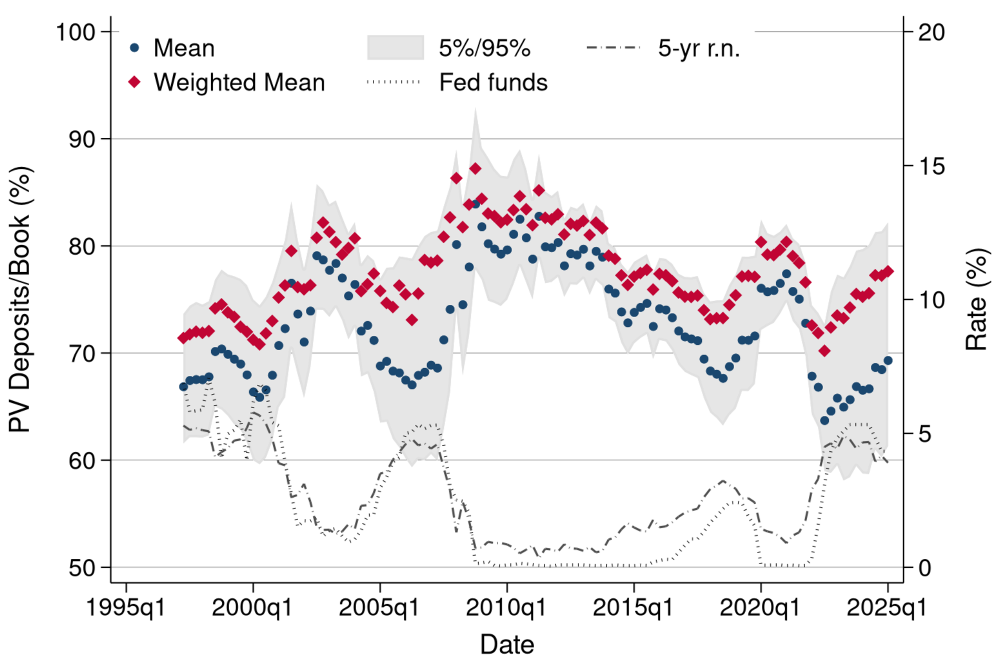
A caveat to our approach is that we can only consider levels of rates that are reflected in the historical data. For instance, long-term rates outside the common support of our estimation would require additional analysis. A more structural approach could perhaps capture novel dynamics that are not in our sample period.

3.3.1 Estimated present values for demand deposits

Figure 3 shows the distribution of demand deposit present values scaled by their reported book values. As anticipated, the present value of demand deposits is consistently below reported book values. On average, the ratio varies between 65 and 85 percent. Demand deposit values are higher for large banks than for smaller banks, as weighted average values are larger than simple average values. This dispersion is driven by higher betas which reflects larger banks' greater reliance on large, non-retail depositors that are more sensitive to changes in interest rates. As discount rates rise, differences in betas increase the cross-sectional dispersion of deposit values and limit the benefits to large banks.

Overall, demand deposit values are quite sensitive to the level of interest rates, especially compared to other bank liabilities (Figure 1b). Reflecting their long effective maturity, deposit values typically have an inverse relation with rates. However, this pattern is not universal. When rates rise and remain elevated, estimted deposit betas also increase. As a consequence, the benefits of higher discount rates can be more than offset by a rise in deposit betas. These results reveal material dynamics in the relation between bank solvency and interest rates that is absent from both current practice and the academic literature.

Figure 3. Distribution of demand deposit values. This figure plots the implied distribution of the present value of demand deposits relative to the book value from 1997:Q2 to present. The chart includes the 5th-95th percentile, the average and the weighted average. The present value of demand deposits is scaled by the book value. The chart includes the 5-year risk neutral yield and the fed funds rate.



3.4 Noninterest expenses

Banks must incur certain expenses to service their customers and achieve the value of their assets and liabilities. In economic terms, these noninterest expenses are an off-balance sheet liability that affects economic capital and by extension, solvency. Examples of such noninterest expenses are administrative expenses, marketing, regulatory compliance costs, and the costs of fixed assets such as technology, ATMs, and branches. However, not all expenses are necessary to maintain the bank — we would like expenses to reflect bank characteristics, but to exclude expenses related to excess loan value and fee-based franchises that we do not include in our measures of economic capital. In this section we outline our approach to generating estimates of necessary expenses and valuing them as a bank liability with details reserved for IA Section D.

We value these costs similar to deposits: as a long-dated perpetuity with a negative growth rate. The present value of necessary expenses for bank i at time t,

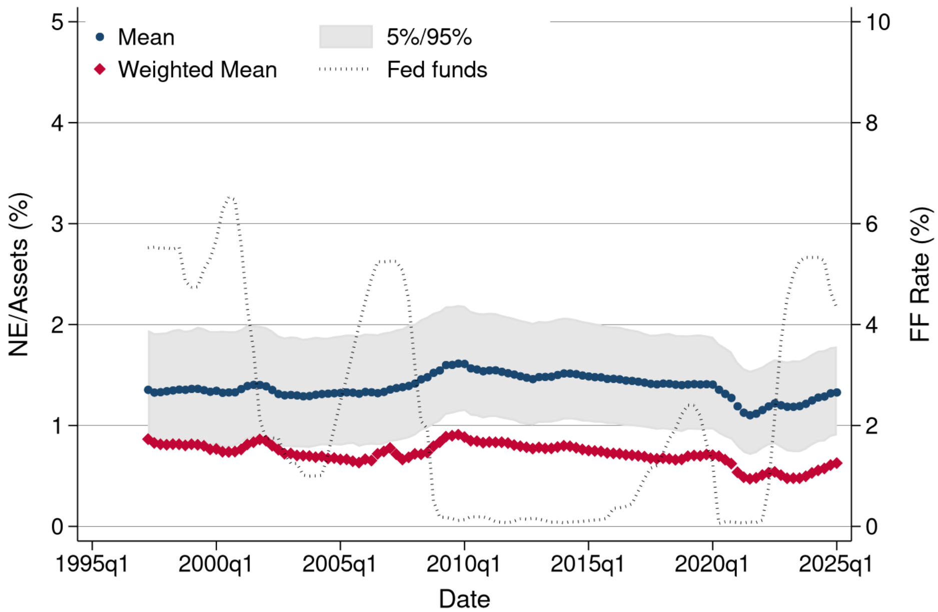
$$PV_{i,t}^{NE} = \left[\frac{c_{i,t}}{y_t^{AAA} + \delta_{i,t}^{NE}}\right] BV_{i,t}^{A}, \tag{5}$$

is the necessary expenses per dollar of book assets, $c_{i,t}$, discounted at the AAA rate used for subordinated debt, y_t^{AAA}. Costs are assumed to decline at the weighted average of the deposit drawdown rate of 5%, and the rate at which a bank's loans mature, $\delta_{i,t}^{NE}$, where the loan maturity rate is based on the weighted average maturity of each bank's loan portfolio. The dollar value is then obtained by multiplying by the dollar value of book assets. The key parameter we estimate is the necessary expense ratio, $c_{i,t}$.

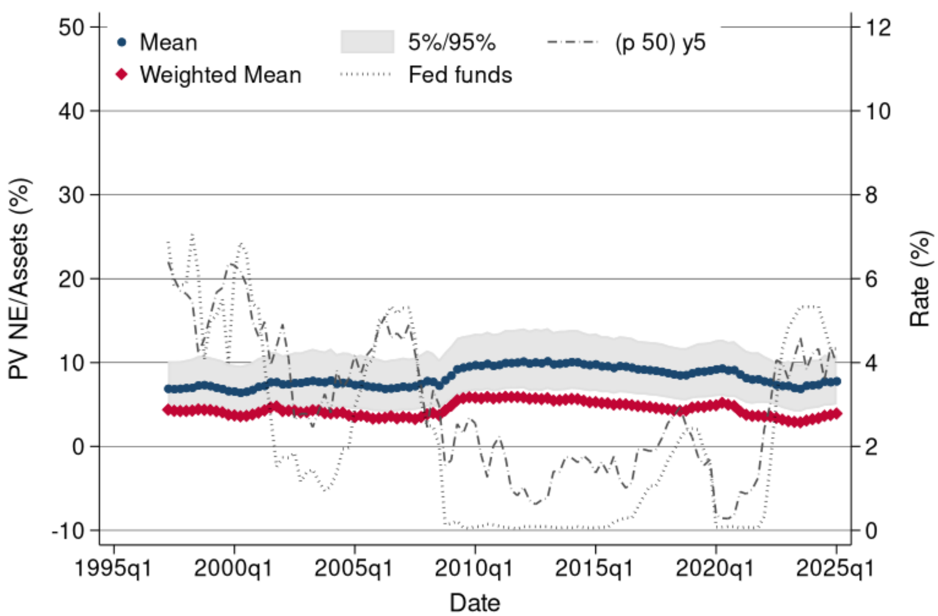
Necessary expenses, $c_{i,t}$: Similar to our estimates of deposit betas, we develop an empirical model of bank expenses using a hedonic regression and then predict values for each bank-quarter conditional on certain assumptions. Our approach generates heterogeneity in costs across banks, consistent with empirical evidence that there are economies of scale in banking (Mullineaux, 1978; Wheelock and Wilson, 2012; Hughes and Mester, 2013) and that costs vary with bank business models. The model accounts for market conditions, bank revenue mix, balance sheet composition, and bank size. Our estimates of necessary expense are increasing in income, demand deposit balances, branches, fixed assets, and loans, but decreasing in interest expense, liquid assets, and size. As with betas, we predict values for each bank by seeding control variables that are consistent with a bank that does not have additional sources of income or loans that generate excess value. Hence, we assume (i) other noninterest income is zero (excluding deposit fees) and (ii) net interest income and loan loss reserves are zero.

Figure 4. Distribution of necessary expenses and their present values over time. These figures plot the implied distribution of the necessary expenses and the present value of these expenses from 1997:Q2 to present. Figure 4a contains the distribution of necessary expense estimates relative to assets. Estimates are calculated using the coefficients in Table IA18 and seeded with bank-specific ratios at each quarter. Interest income is assumed to be equal to interest expense, noninterest income (excl. deposit fees) are set to zero, and loan loss reserves are set to zero. Figure 4b contains the distribution of present values based on Eq. 5. Each chart includes the 5th-95th percentile, the average and the weighted average. The figures also include the five-year risk-free rate and the fed funds rate.

(a) Necessary Expenses



(b) PV Expenses



3.4.1 Estimated present values of expenses

Figure 4 illustrates the distribution of necessary expenses and the present value of necessary expenses over time. Necessary expenses, Figure 4a, primarily range from 0.8-2% of assets. The results are consistent with economies of scale as the weighted average is roughly half that of the simple average. They are also roughly consistent with estimates of deposit servicing costs in the literature, particularly given we are seeking to capture a broader set of expenses than those solely related to deposit costs.[17] The present value of expenses, Figure 4b, range from 4-10% and reflect the distribution of expenses. Both expenses and present values are relatively stable over time.

3.5 Liquidity and stress

With estimates of present value in hand, we can calculate our base case measure of economic capital, EC, and then sensitize this calculation to specific assumptions so as to determine whether the level of EC is robust to changes in depositor behavior or other market conditions such as interest rates or credit spreads.

3.5.1 Funding liquidity

Changes in funding liquidity, specifically the timing of deposit withdrawals, can significantly impact the value of bank liabilities. If banks lack sufficient asset value to accommodate withdrawals, then depositors may run to avoid incurring losses, which lowers economic capital. This behavior is typically associated with uninsured or sophisticated depositors that are most responsive to information about bank solvency (e.g., Iyer and Puri, 2012).

To assess the impact of depositor behavior for economic capital, we consider two economic capital scenarios for deposit liabilities: one in which we assume that depositors behave as they typically do, denoted EC, and another in which uninsured demand deposits are given a deposit beta of one, R-EC. The latter effectively assumes that the banks must substitute uninsured deposits with funds that pay the prevailing discount rate. This repricing of uninsured, demandable liabilities captures our notion of funding or liquidity risk by revaluing deposits to reflect their immediate replacement. The impact of this varies by banks and over time depending on deposit betas and a bank's reliance on uninsured deposits. Banks with sufficient asset value will be able to borrow at prevailing rates and still have ample economic capital, whereas banks that have low economic capital in this scenario may not be able to borrow at typical rates and are effectively insolvent or at least at enhanced risk of default.

[17] Van den Heuvel (2024) estimates costs of 1.22% from 1986 to 2000 and Hanson et al. (2015) finds an average of 0.81 percent from 1984 to 2012 using hedonic regressions.

Figure 5 summarizes our estimates of EC and R-EC. EC declines prior during the GFC and slowly rebounds to levels that are higher than the pre-GFC period. Large and small banks appear to have similar average EC over time, although small banks are slightly lower during the period from 2010 through 2018. When we reprice uninsured deposits, economic capital is strictly lower. Banks no longer appear better capitalized post-GFC and large banks in particular appear to have lower EC than small banks, particularly from 2015 onwards. Hence, incorporating the solvency risk inherent in funding liquidity into an assessment of solvency has a material impact on assessments of banks' health. In the next section, we test the information content of these measures and discuss the implications for bank risk.

3.5.2 Market risk and stress scenarios

EC measures are readily sensitized to a variety of market shocks to assess the resiliency of the banking sector. We consider two such shocks: a parallel shift in the yield curve (rf) and a shock to credit spreads (rp). Conditional on funding liquidity, we can describe the exposure of each bank at each point in time to economic conditions by scaling by book assets and taking the derivative of Equation 1,

$$
\begin{aligned}
\frac{\mathrm{dEC}}{Assets} &= \beta^A_{rf}\mathrm{d}rf + \beta^A_{rp}\mathrm{d}rp - \beta^L_{rf}\mathrm{d}rf \\
&= \underbrace{(\beta^A_{rf} - \beta^L_{rf})\mathrm{d}rf}_{\text{Interest rates}} + \underbrace{\beta^A_{rp}\mathrm{d}rp}_{\substack{\text{Credit}\\\text{spreads}}} \quad .
\end{aligned} \tag{6}
$$

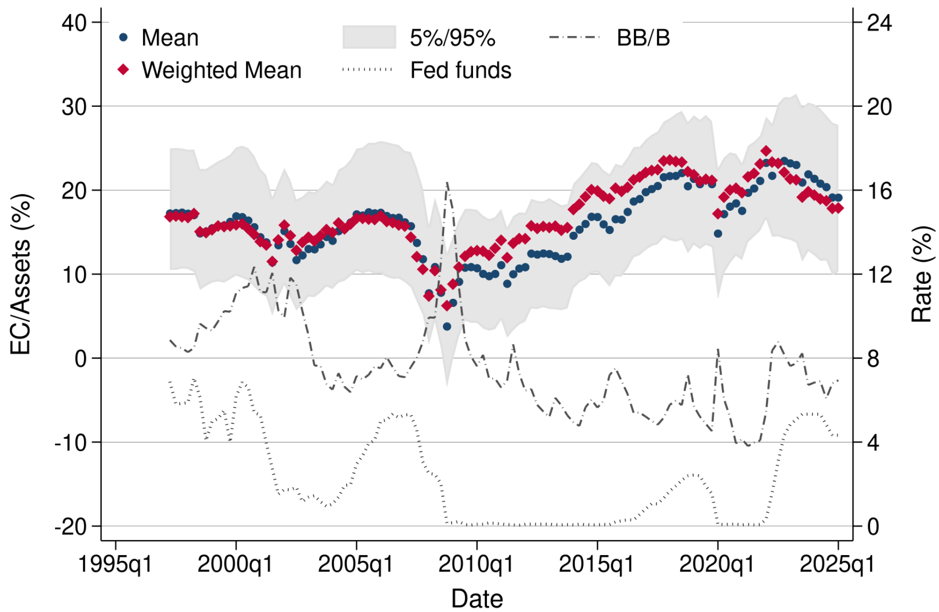
The asset and liability betas are a weighted linear combination of relevant durations, D. Where the weights, ω, are the ratio of the relevant present value to book assets. Durations are the same as those used to calculate present values. For securities portfolios we use the maturity implied by the Call Report. Asset and liability betas for a specific bank quarter are,

$$
\begin{aligned}
\beta^A_{rf} &= \omega_{\text{Loans}} D_{\text{Loans}} + \omega_{\text{RFSec.}} D_{\text{RFSec.}} + \omega_{\text{RPSec.}} D_{\text{RPSec.}} \\
\beta^L_{rf} &= \omega_{\text{Debts}} D_{\text{Debts}} + \omega_{\text{Deposits}} D_{\text{Deposits}} + \omega_{\text{Expenses}} D_{\text{Expenses}} \\
\beta^A_{rp} &= \omega_{\text{Loans}} D_{\text{Loans}} + \omega_{\text{RPSec.}} D_{\text{RPSec.}},
\end{aligned}
$$

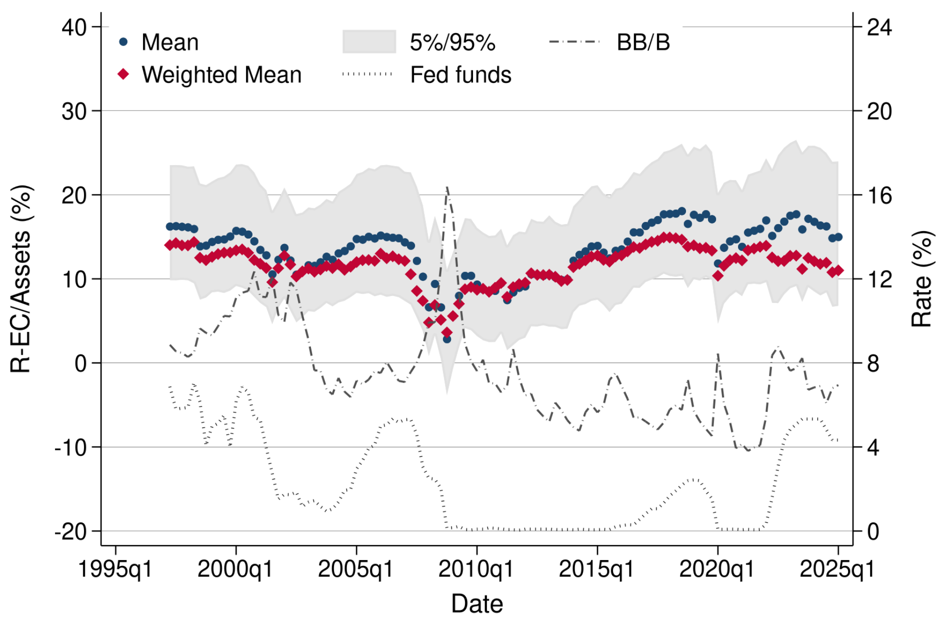
where securities are decomposed into risk free (RF) and risky (RP) portfolios. Risk-free securities are exposed to interest rate shocks whereas risky securities are exposed to both interest rates and credit spreads. These betas vary by bank and over time reflecting bank specific changes in composition. Positive betas imply that when rates (or spreads) increase

Figure 5. Distribution of EC and R-EC. These figures plot the implied distribution of EC and R-EC from 1997:Q2 to present. Figure 5a depicts the present value of EC to total assets. Figures 5b depicts the present value of R-EC to total assets where uninsured deposits recieve a beta of one. Each chart includes the 5th-95th percentile, the average and the weighted average by quarter. The figures also include the five-year risk neutral yield and the fed funds rate.

(a) EC



(b) R-EC



that the corresponding value also increases. Negative betas imply that an increase in rates lowers value. With respect to credit risk, betas are scaled to reflect the risk of the loan portfolio. For instance, a credit shock of 100 basis points to the AA spread is 2.5 times larger for a portfolio discounted at the BB/B spread. A time-series representation of both exposures can be found in Figures IA33 and IA34. We explore these betas further when we consider applications in Section 4.2.

4 Results

With estimates in hand, we validate the information content of economic capital by testing its ability to predict bank failure. Then, we consider applications of economic capital for research and policy.

4.1 Validation

We validate EC and R-EC by testing their ability to predict bank failure at long horizons. Our sample, based on the FDIC Failed Bank List, includes 460 failures from 1997 to 2024 across diverse economic conditions, with over 80% occurring during 2008-2012 amid housing-related credit losses. We specifically examine interest rate-driven failures to test robustness to atypical shocks. We compare EC and R-EC to TCE and market-adjusted TCE (MATCE). TCE is a close complement to regulatory measures of capital such as CET1 and Tier 1, but TCE is available for the entire sample period. To obtain MATCE, we adjust TCE for the difference between the present value and the book value of assets. For each capital measure, we calculate percentiles in each quarter of the six years before failure or distress, then plot average percentiles for failing/distressed banks.

Figure 6a shows that economic capital measures provide more timely signals of risk than the TCE-based measures. As early as six years prior to failure, the average failed bank has an EC or R-EC in the lowest tercile. Moreover, the failed banks' average percentile begins to deteriorate more than five years prior to failure, then accelerates around the two-year mark. While there is little difference between EC and R-EC in the full sample, we will show that R-EC is the more robust measure by incorporating risks that emerged in March of 2023.[18] In contrast, TCE and MATCE percentiles are consistently in the middle tercile and are stable

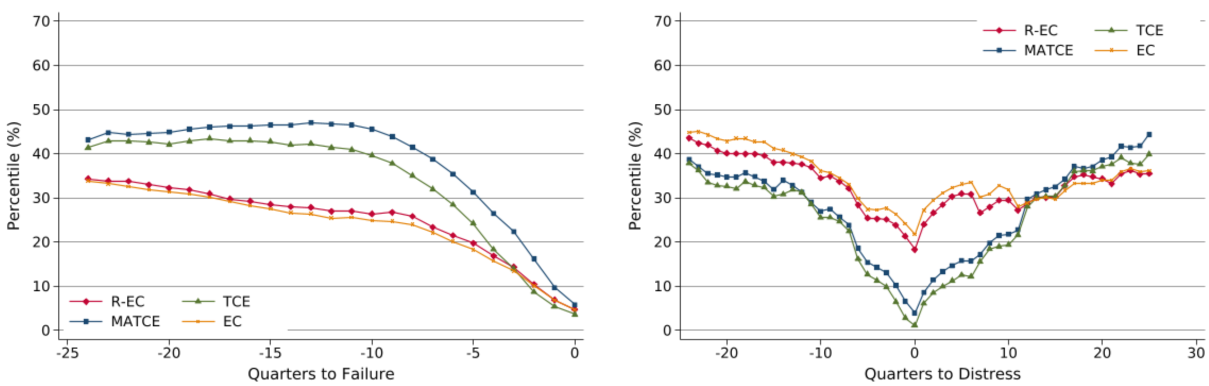
[18] A key reason for the lack of differentiation in the full sample could be the Temporary Liquidity Guarantee Program (TLGP) that was in place from October 14, 2008 through December 31, 2010 and was effectively extended by the Dodd-Frank Act through December 31, 2012. In total, this period contains more than 80% of bank failures in the sample. The TLGP and its predecessors effectively guaranteed all noninterest bearing transaction accounts for this period, eliminating the incentive to run by otherwise uninsured depositors.

or increasing until about 10 quarters before failure. All metrics converge at or below their 5th percentiles in the final quarters prior to failure; this is expected given that supervisors close banks with sufficiently low TCE under Prompt Corrective Action. Economic capital's key advantage is identifying insolvency risk years before conventional metrics — a longer horizon than typically examined by off-site supervisory models (Cole and Gunther, 1998) or recent academic work on bank failures Correia et al. (2025).

Do EC and R-EC also generate fewer false positives than TCE-based measures? Figure 6b examines banks that became distressed by did not fail, where we define a distressed bank-quarter as the first quarter a bank's TCE ratio falls below 3 percent.[19] From six years before through 10 quarters after the distress quarter, EC and R-EC percentiles exceed those of TCE and MATCE, indicating lower solvency risk. The gap between the economic capital and TCE-based measures widens sharply in the two years before peak distress. TCE and MATCE percentiles fall sharply, while those for EC and R-EC decline only moderately. This suggests our economic capital measures better distinguish banks with sufficient value to survive via retained earnings, new funding, or as an acquisition target.

Figure 6. Solvency measures prior to bank failure and bank distress This figure plots the percentile for various solvency metrics in the run-up to bank failure (Fig. 6a) and around periods of bank distress (Fig. 6b). For bank failures we consider the 6 years prior to bank failure and for bank distress we consider the 6 years prior to and following the distress quarter. Failures are obtained from the FDIC and distress is strictly for banks that do not fail but have a TCE-ratio less than 3%. Percentiles are calculated quarter-by-quarter. Comparing the two events illustrates the ability of EC to differentiate between banks that fail versus banks that are distressed based on conventional metrics but do not fail.

(a) Failures **(b)** Distress (w/out failure)



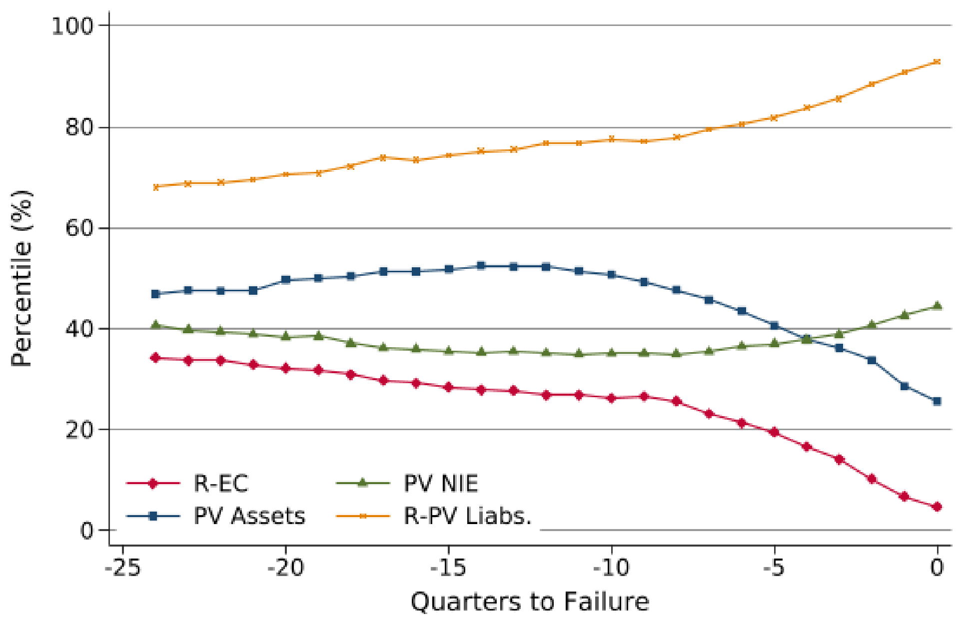
To understand which components drive the superior performance of economic capital we decompose R-EC into its constituent parts, Figure 7: the present values of assets, liabilities, and necessary expenses, each scaled by total assets gross of loan loss reserves.[20] Liability

[19]This definition is broadly consistent with the regulatory designation of a bank being "Significantly Undercapitalized" (Federal Deposit Insurance Corporation, 2023, Chapter 5, p. 5-1).

[20]We include loan loss reserves in the denominator so that the ratio reflects deterioration in credit quality

values emerge as the key differntiator. Asset values remain in the middle of the distribution until three years prior to failure. In contrast,the present value of liabilities is in the upper tercile six years prior to failure and rises throughout the pre-failure period, peaking near the 90th percentile in the quarter before failure. Non-interest expense percentiles begin below the industry median but rise in the final 10 quarters. These patterns reveal that economic capital's predictive power stems primarily from incorporating liability values, which capture banks' funding costs — information absent from TCE-based metrics.

Figure 7. Components of R-EC prior to bank failure This figure plots the percentile for the components of R-EC in the run-up to bank failure in order to illustrate the importance of both assets, liabilities and expenses in assessing risk. Percentiles are calculated quarter-by-quarter.



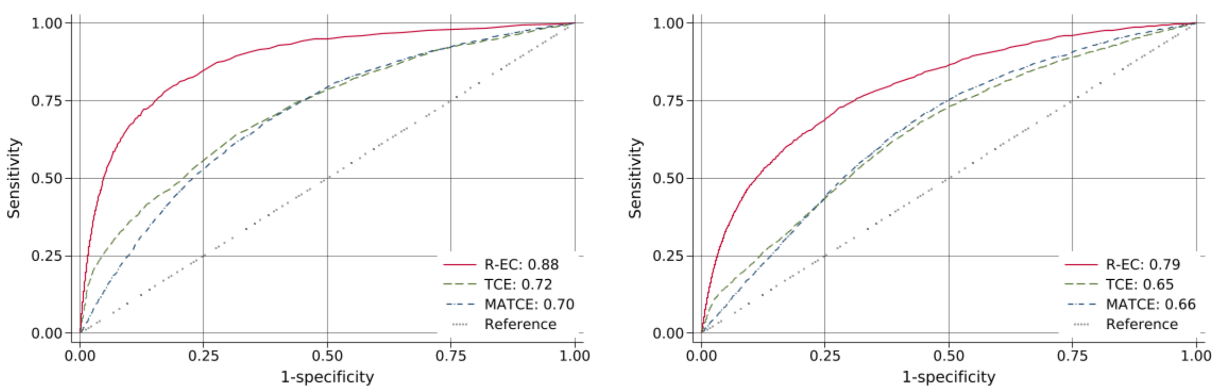
We formally test the predictive power of R-EC versus the TCE-based metrics using logit models. Supervisors are required to intervene at banks with regulatory capital, which is closely related to TCE, below certain levels, so at short horizons a low TCE should perfectly predict failure. To account for this, we estimate the ability of R-EC, TCE and MATCE to predict bank failure over a long time-horizon but exclude the next four quarters. In this way, we capture the long-term information content of capital measures on bank solvency. Using our logits we calculate Receiver Operating Curves (ROC) and compare the Area Under

that *lowers* book assets. When loan loss reserves rise both the present value of assets and the book value of assets mechanically decline. Hence, rising reserves will result in a stable ratio of PV-to-book even though asset values are declining. Similarly, if we were to scale liabilities by just assets, rising reserves would mechanically increase the PV of liabilities to assets (even if liability values are stable). Hence scaling by book assets plus reserves improves inference as to which values are rising/falling in advance of failure.

the Curve (AUC) to assess which metrics are more informative. The AUC summarizes the probability that a model will identify a bank that fails versus a bank that does not fail and the curve plots the true positive rate (e.g., sensitivity) against the false positive rate (1-specificity).

Figure 8. Receiver Operating Curves for solvency measures: 8- and 16-quarter horizons This figure plots ROCs for a variety of capital measures. ROCs are based on a logit model with a failure dummy as the dependent variable and a lagged measure of capital as the independent variable. We consider two dependent variables: a dummy equal to one if a bank fails in the 4-8 quarters in the future and a dummy equal to one if a bank fails in 4-16 quarters. Alternative specifications that include failure in the next four quarters can be found in Figure IA31. Line labels also report the AUC.

(a) 8-quarter **(b)** 16-quarter



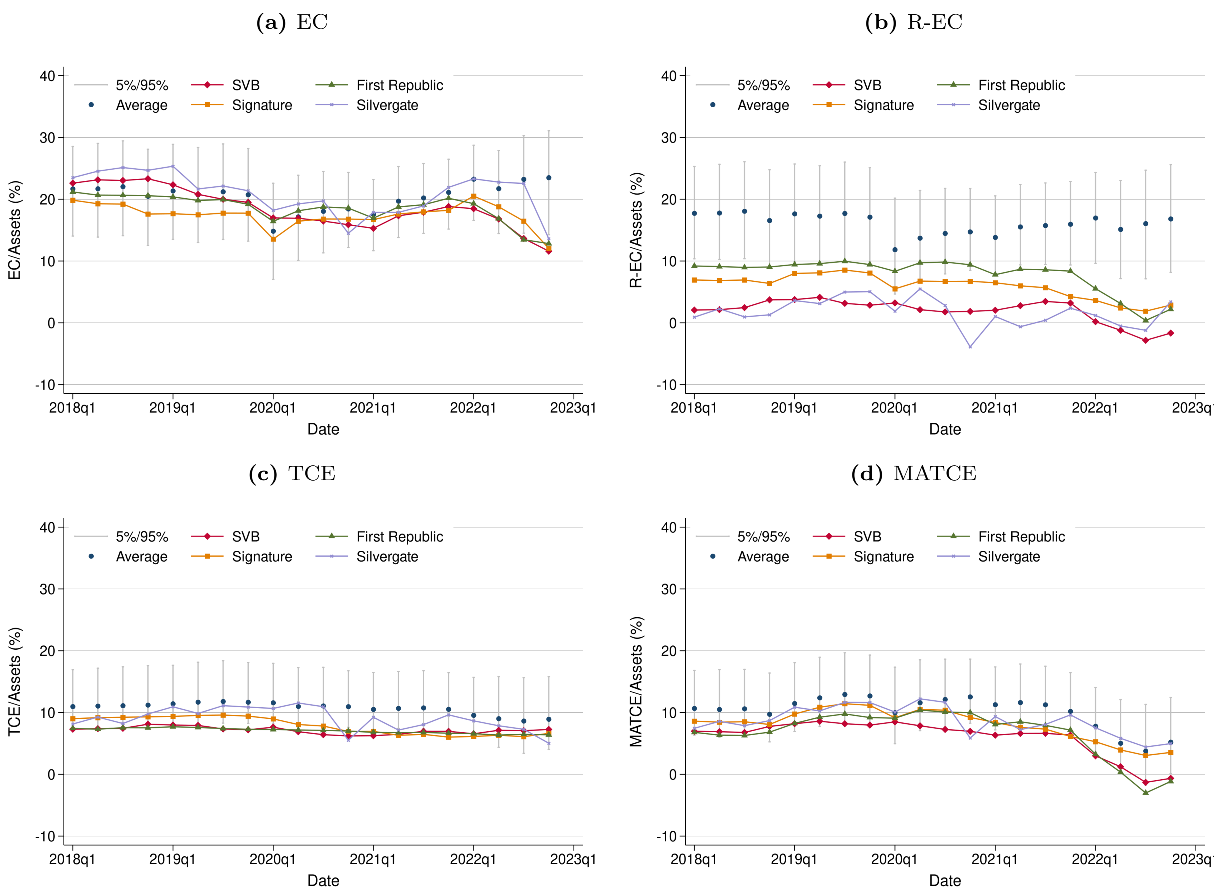
At both horizons, R-EC is significantly more accurate than the alternative capital metrics, Figure 8. At the 8-quarter horizon, Figure 8a, the AUC for R-EC is 0.88 versus the next closest metric, TCE, at 0.72. The higher curve over the vast majority of specificity levels illustrates how much more accurate R-EC is for evaluating failure risk. At the 16-quarter horizon the results are similar but attenuated, Figure 8b. The AUC for R-EC is 0.79 versus the next closest metric, TCE, at 0.65. Alternative formulations in Internet Appendix Section F also find R-EC is a superior predictor. Across all specifications, an incomplete marking-to-market (MATCE) does *worse* than a pure accounting measure (TCE) or a measure that fair values both sides of the balance sheet (R-EC).

4.1.1 Interest rate risk: March 2023

Most bank failures in our sample stem from credit risk; however, the 2023 banking instability was driven by interest rate risk. To assess whether economic capital captures diverse risks, we examine how well it identified the four large banks that failed in early 2023: Silicon Valley Bank (SVB), First Republic Bank, Signature Bank, and Silvergate Bank.

Figure 9 plots EC, R-EC, TCE and MATCE for these four banks alongside the 5th/95th percentile range for the banking sector. The capital measures are scaled by book assets. Figures 9a and 9b show the path of EC and R-EC, respectively, from 2018 to 2022:Q4, just before March 2023. As shown in Figure 9a, the EC of the failed banks falls sharply as rates rise in 2022, falling from near the industry average to around the 5th percentile. While low, these banks are not stark outliers with respect to the overall distribution of banks: all four banks have positive EC ratios that exceed the 5th percentile of the distribution at the end of 2022. However, once we account for the repricing risk in uninsured deposits through R-EC, Figure 9b, we find that the four banks that fail have low economic capital in both relative and absolute terms up to five years before the emergence of funding stress.

Figure 9. Failed bank solvency measures: 2018:Q1 - 2022:Q4 This figure plots solvency metrics for four banks that failed in March of 2023 as well as the mean and 5th-95th percentile ranges for the banking sector. Figure 9a depicts the economic capital-to-assets (EC); Figure 9b the run economic capital-to-assets (R-EC) where uninsured demand deposits are assigned a beta of one; Figure 9c the TCE-to-assets (TCE) and Figure 9d the MATCE-to-assets (MATCE).



Other measures of solvency, such as TCE or MATCE, where assets (but not liabilities) are marked-to-market, do not generate similar signals of distress for these firms. TCE ratios, Figure 9c, remain stable even as the market value for assets deteriorates in 2022 — if anything, TCE ratios for SVB and Signature moved from the 5th percentile towards the industry average during this period. When we mark-to-market the assets using our calculations, Figure 9d, the distribution of MATCE ratios falls in 2022, but the four failed banks are not outliers. This demonstrates the shortcomings of marking just one side of the balance sheet to market – it masks important underlying differences in funding exposures across banks, providing far too broad a signal to meaningfully identify the banks that are truly at risk.

Table 2 further demonstrates the benefits of economic capital by examining R-EC, MATCE and our measure of IRR, β_{rf}, as of the 2021:Q4, before market stress emerged. The table focuses on the 135 banks with assets greater than $10 billion to create a size comparable peer group. Banks are ranked from lowest (1) to highest (135) to assess whether the failing banks appear as outliers. The first two columns show that Silvergate, SVB and Signature had the three lowest measures of R-EC prior to the hiking cycle, while First Republic was the tenth lowest.

Table 2: 2021:Q4: Stressed Economic Capital vs. Other Metrics. This table summarizes R-EC, MATCE and interest rate risk for banks that failed in 2023:Q1 as of 2021:Q4. The table reports the rank relative to banks with more than $10bn in assets as well as the level of capital to assets (in percent). Ranks are reported from low to high. R-EC is the economic capital in a deposit run scenario. β_{rf} is the change in R-EC for a 100bps increase in the level of the yield curve. Stress R-EC is the R-EC assuming a 200bps increase in rates. Stress MATCE is the MATCE assuming a 200bps increase in rates.

	R-EC		β_{rf}		Stress R-EC		Stress MATCE	
	Rank	%	Rank	%	Rank	%	Rank	%
Silvergate	1	2.37	3	-2.74	2	-3.10	83	2.39
Silicon Valley	2	3.21	2	-3.25	1	-3.29	29	-1.19
Signature	3	4.24	18	-1.02	4	2.21	94	2.93
First Republic	10	8.37	1	-3.29	3	1.79	22	-1.91
Industry (> $10b)	69.45	13.78	69.39	0.22	69.50	14.21	67.82	1.47

The third an fourth columns of Table 2 show the R-EC's exposure to interest rates. Banks that failed had the three of the four highest exposures to rising rates. Silvergate appeared less exposed, ranking 18th, whereas the bank with the fourth highest exposure to rising rates does not fail (R-EC 13%). Thus, interest rate exposure is an insufficient statistic to assess the bank's health when rates rise; these risks must be considred relative to capital levels. Indeed, columns five and six demonstrate that when our measure of interest rate risk is applied to R-EC we can uniquely identify the banks that fail. When we stress R-EC to a 200bps increase in rates, the failed banks have the four lowest measures of economic capital, uniquely identifying them more than a year before failure. Stressing only assets, columns seven and eight, fails to identify these banks as outliers.

Overall, the results in this episode and the broader sample support the notion that economic capital is more informative of bank solvency, particularly at long horizons. The valuation of bank liabilities are especially important by differentiating across maturities and deposit bases. In the broader sample liability values indicate less-well capitalized banks long in advance and in the interest rate risk episode exposure to uninsured deposits are a critical determinant of survival.

4.2 Applications

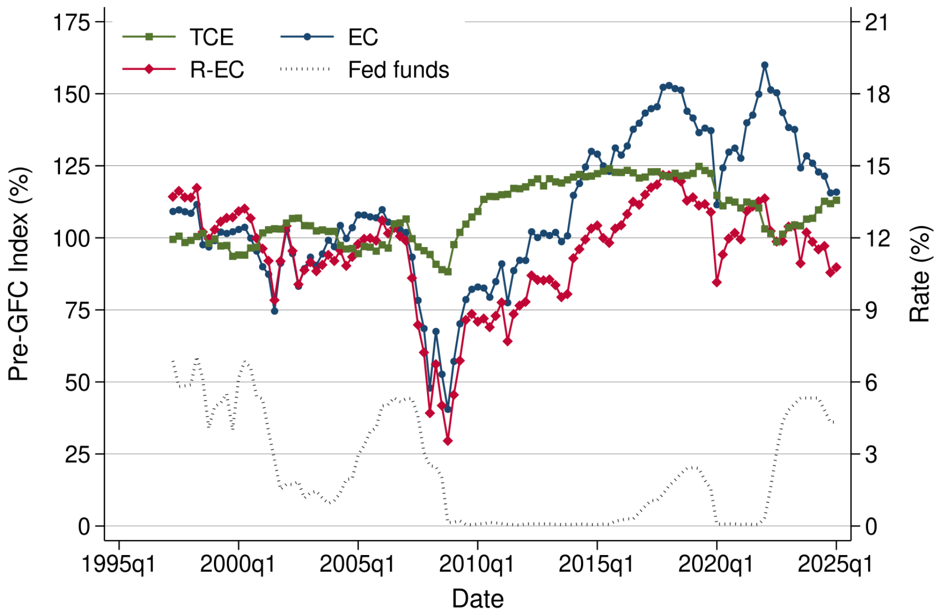
As an alternative measure of solvency, EC has the potential to impact policy and research. We propose several areas in which insights from our measure could be applied along with evidence that suggests distinct differences from current methods and the extant literature.

4.2.1 Financial stability

Besides the potential benefits to microprudential supervision that are illustrated in the prior section, the notion of economic capital is relevant to macroprudential assessments of the banking sector, including areas where the current practices can fall short (Hanson et al., 2011). To illustrate how our framework can improve assessments of financial stability, we compare the evolution of EC and R-EC to TCE-based metrics of capital, Figure 10. Industry TCE increases sharply during the GFC and remains roughly 25 percent higher than its pre-GFC average until the emergence of COVID and the rate hikes of 2022. Meanwhile, EC and R-EC take much longer to return to pre-GFC levels following 2009, suggesting that the banking industry was not as well capitalized as TCE suggested for the period from 2010 to 2015. Low EC is consistent with lagging stock prices and restrained loan growth during this period. The reason EC lags TCE is due to the value of deposits, which are elevated when rates are low, Figure 3. The return of economic capital to pre-GFC levels corresponds with an uptick in long rates.

We can sensitize our EC measures to various scenarios to obtain industry exposure to key financial risks. The difference between R-EC and EC summarizes the exposure of banks to uninsured deposits in units of capital. In this way, we can also use the sensitivity of EC, Equation 6, to obtain the exposure of banks to credit spreads and risk-free rates. Figure 11 depicts differences in the R-EC distribution over the sample period. The gap between EC and

Figure 10. Industry capital ratios over time. This figure plots the evolution of industry capital ratios over time. Industry ratios are the weighted average of each individual bank. For comparison purposes, we index ratios to their pre-GFC average (1997:Q2-2007:Q1).



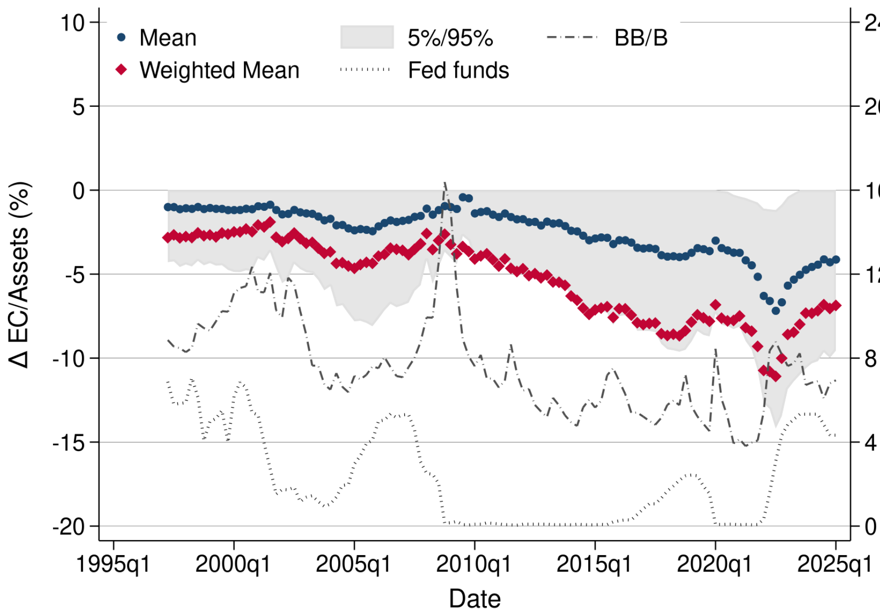
R-EC has increased since the GFC, Figure 11a, reflecting the growing reliance on uninsured deposits, particularly for the largest banks, which peaked in the period prior to March 2023. As shown in Figure 10, after accounting for deposit run risks, there is little evidence that the solvency of the banking industry has improved. The comparative stability of R-EC ratios over time reflects the offsetting effects of increased equity in the banking system (evident in the increase in EC ratios) and the growing reliance on uninsured deposits.

Figures 11b and 11c illustrate the evolution of the banking industry's exposure to interest rate risk and credit risk, respectively. Exposure to interest rates is highly sensitive to assumptions deposit repricing. As illustrated in Figure 11b, IRR for R-EC generally ranges around zero, consistent with the off-setting sensitivity of both assets and liabilities to interest rates (Flannery, 1981; Flannery and James, 1984; Drechsler et al., 2021). However, the figure suggests that there is significant variation in the cross-section and time-series. Following the GFC, banks are positioned to benefit from an increase in rates, but, by the latter half of 2022, this potential reverses, suggesting that the level of capital was not as high as it would have appeared using unstressed (EC) or conventional (TCE) capital measures.

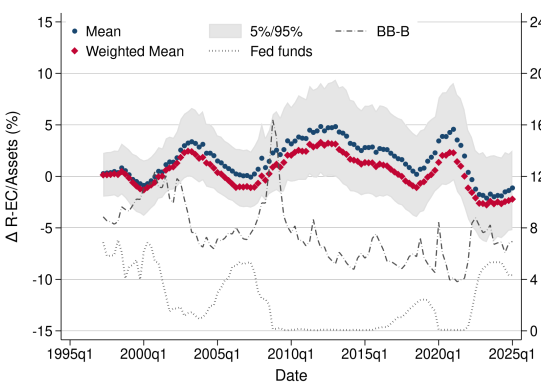
The extant literature on interest rate risk tends to draw sharp conclusions as to the exposure of the banking sector to interest rates (for instance DeMarzo et al. (2024) vs. Drechsler et al. (2021)). But, our measure rejects a simple narrative as we find it is highly

Figure 11. Distribution of risk exposures over time. These figures plot the impact of stressing EC measures to demonstrate the evolution of risk exposures in the banking industry from 1997:Q2 to present. Higher numbers reflect a benefit to EC, lower numbers a cost. Figure 11a depicts the difference between R-EC and EC; Figure 11b the difference between R-EC when the yield curve increases by 200bps and R-EC; and, Figure 11c the difference between R-EC where the risk spreads increases by 250-500bps and R-EC. Each chart includes the 5th-95th percentile, the average and the weighted average as well as the BB-B yield and the fed funds rate.

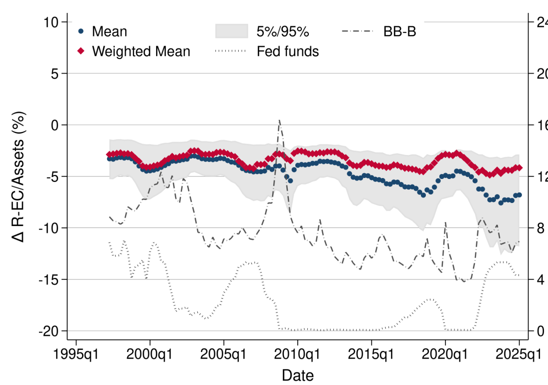
(a) Uninsured deposits



(b) IRR: $\beta_{rf} \times$ 200bps



(c) Credit spreads: $\beta_{rp} \times$ 250bps-500bps



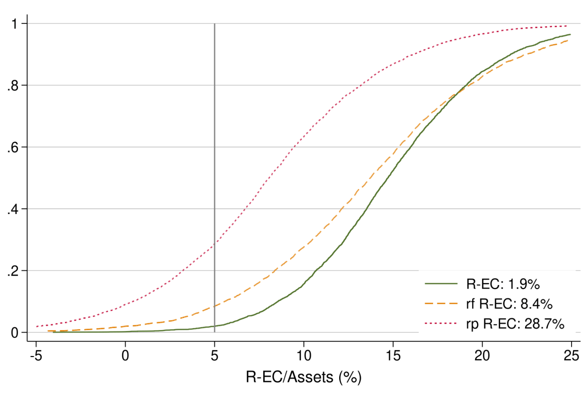
heterogeneous and dynamic. The average sign changes depending on the level of rates and bank portfolio composition. Central to this dynamism is the nonlinear relation between certain asset and liability values with respect to rates. Mortgages possess negative convexity arising from prepayment and deposits possess positive convexity arising from forward-looking deposit betas. Hence, the natural hedge to rate fluctuations varies as rates evolve.

In contrast to interest rates, credit spreads only impact assets, Figure 11c. Hence, an increase in spreads always poses a risk to capital. Exposure to credit spreads are elevated in the post-GFC period, with more variance in the cross-section of banks, once again suggesting that the banking sector is not as resilient as suggested by standard measures. This is despite the trends away from on-balance-sheet lending (Buchak et al., 2024) and is driven by a growing exposure to higher interest rate loans and loans with longer duration relative to earlier periods. In particular, small banks appear to have increased their exposure to credit risk relative to large banks and their own history.

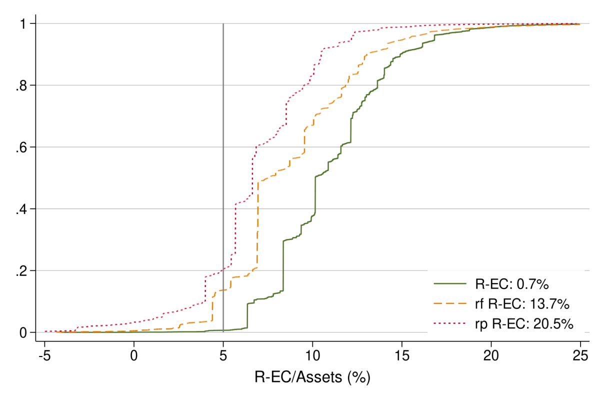
Following significant reform post-GFC, risks that were well-captured by the regulatory framework appeared to recede, whereas deposit funding risk built-up at large banks and credit risk grew at smaller institutions. As of 2025:Q1, we can assess the asset-weighted distribution of R-EC under various scenarios and infer the overall exposure of the industry to market shocks, see Figure 12. The relatively low levels of economic capital and current risk exposures suggest that significant increases in either interest rates or credit spreads would impair a meaningful portion of the industry. From a financial stability perspective, this is particularly concerning as it relates to the largest banks — there is a high concentration of banking industry assets that have low R-EC if rates increase sharply.

Figure 12. Cumulative distribution of R-EC under stress in 2025:Q1. This figure plots the cumulative distribution of R-EC in 2025Q1 and the distribution assuming a 200bps level shock to rates (rf) or a 250bps increase in the AA spread (rp). The vertical line indicates a 5% economic capital to assets ratio. Labels indicate the percent of assets below 5%.

(a) Equal weighted



(b) Asset weighted



Overall, the economic capital framework provides a rich lens with which to evaluate financial stability and suggests several additional areas of research. For instance, the impairment of EC at low rates suggests that there are potential offsetting channels of expansionary monetary policy (such as 'low-for-long' interest rates) that have not been fully explored. Moreover, the dynamism in interest rate risk dynamics highlight the potential for a bank-specific transmission channel for monetary policy that is more nuanced than current theories.

4.2.2 Capital and credit supply

The literature on financial shocks has identified important relations between regulatory capital and bank credit supply. For instance, banks that appear to be deficient in regulatory capital or liquidity constrain lending (e.g., Peek and Rosengren, 1997) which can result in real effects to the economy (Ashcraft (2005), Khwaja and Mian (2008), Chodorow-Reich (2014)). Economic capital presents an alternative measure of bank health that is less directly related to regulatory frameworks and more closely aligned with bank's forward-looking risk management and the underlying economics of the business. Hence, economic capital may uniquely capture an important determinant of the capacity for the banking sector to intermediate funds from savers to borrowers.

Table 3: Predicting loan growth using capital metrics. This table reports coefficients from a regression of bank-level loan growth on EC and TCE from 1997 to present. Loan growth is measured as the annualized log change in growth over eight quarters, winsorized at 5th/95th percentiles. EC is the ratio of EC to assets in percent lagged eight quarters. TCE is the ratio of TCE to assets in percent lagged eight quarters. Standard errors are clustered by date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
EC $_{t-8}$	0.22***	0.34***	0.20***	0.39***
	(0.04)	(0.06)	(0.03)	(0.04)
TCE $_{t-8}$	-0.37***	0.77***	0.06	0.13
	(0.03)	(0.13)	(0.04)	(0.11)
Observations	571382	77916	571247	77346
Adj. R^2	0.02	0.05	0.35	0.51
Fixed Effects	None	None	Bank & Time	Bank & Time
TCE Values	All	$< 7.5\%$	All	$< 7.5\%$
Y mean	6.87	7.98	6.87	7.98

To illustrate a potential role for economic capital in credit provision, we regress loan growth on lagged levels of EC and TCE.[21] Typically, regulatory capital is perceived as costly when it approaches constraints (e.g. Plosser and Santos, 2023), therefore we consider these relations for the full sample and the sample of banks that have a TCE ratio less than 7.5%.

[21]Here, we focus on EC as opposed to R-EC as it reflects the "business as usual" level of capital a bank is likely to manage toward. However, it is interesting to consider what scenarios may (or may not) impact lending decisions more broadly.

Predictive regressions between capital and lending are naturally subject to identification concerns, chief among them is omitted variable bias. Capital may reflect bank- or time-specific factors that determine lending behavior such as the risk appetite of an institution or the overall state of the economy. Therefore, we consider regressions that include both bank- and time- fixed effects to account for macroeconomic conditions as well as persistent features of a bank that impact lending.

The estimated coefficients are summarized in Table 3. Overall, we find that EC predicts future loan growth. Across all specifications the coefficient on EC is positive and statistically significant, even in the presence of the full complement of fixed effects, Column (4). In contrast, TCE only exhibits a positive correlation with loan growth when we focus on the set of banks that are constrained by regulatory capital and we exclude fixed effects, Column (3). The predictive power of EC suggests that notions of economic capital would be useful in understanding bank lending behavior more broadly, particularly as it may relate to changes in the stance of monetary policy that have a significant impact on the expected profitability, and by extension valuation, of bank assets and liabilities (e.g., Jiménez et al., 2012; Gomez et al., 2021).

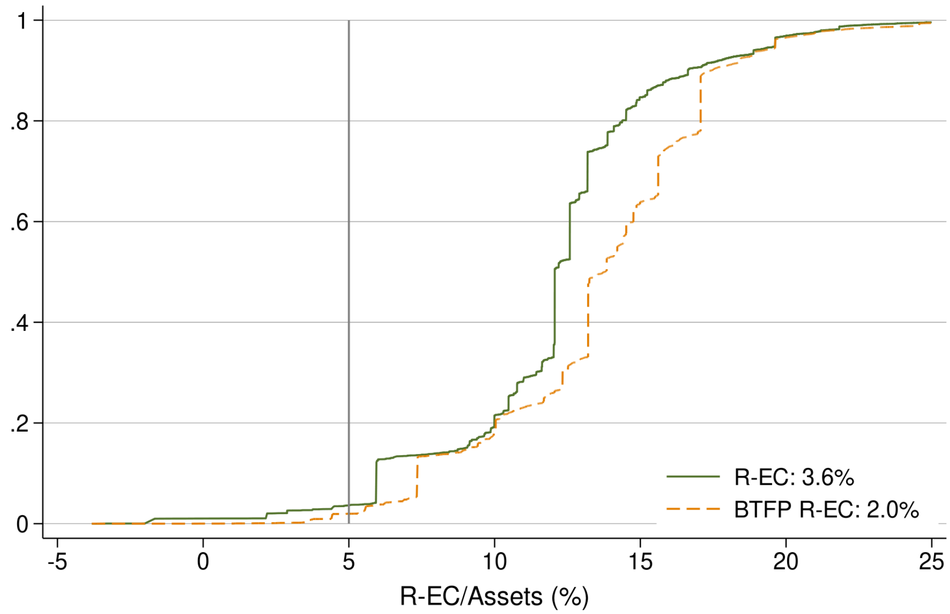
Banks with high EC before a rate increase may be better positioned to sustain lending growth because they possess genuine funding advantages — low deposit betas that reflect sticky, relationship-based deposits.

4.2.3 Policy evaluation

Economic capital can be used to explore the impact of potential interventions on banking sector stability. During periods of market turmoil, policy makers need tools to understand policy impact. For instance, following the events of March 2023, the Federal Reserve established the Bank Term Funding Program (BTFP) to lend against the par value of securities. An important consideration for a program like the BTFP is whether it helps banks that are likely to fail versus subsidizing relatively healthy banks. Overall, the average impact of the BTFP on R-EC is small — around 30bps — however it is important to assess the benefits for at-risk banks rather than the average bank.

To evaluate the impact of the BTFP, we plot the asset-weighted distribution of economic capital in the banking sector and then consider a simple counterfactual that estimates the distribution under the BTFP. Figure 13 illustrates the distribution of R-EC in 2022Q4 as well as the distribution where the present value of securities is equal to their book value. As expected, the overall distribution shifts to the right as the value of bank assets increases. The percentage of banks below the 5% threshold decreases from 3.6% to 2.0%. These values would revert when the program concludes. In general, this analysis suggests that the BTFP

Figure 13. Asset weighted distribution of R-EC and the BTFP. This figure plots the cumulative distribution of R-EC in 2022Q4 and the distribution assuming implementation of the BTFP. Both distributions are asset weighted. The vertical line indicates a 5% economic capital to assets ratio. Labels indicate the percent of assets below 5%.



only slightly reduced the share of industry assets held by banks most at risk of failure – those with low levels of R-EC – though there is one large bank at roughly 6% of R-EC that appears to have benefitted meaningfully. The R-EC distributions demonstrate that the vast majority of the improvement in capital is for banks with relatively healthy levels of R-EC above 10%. Analysis like this could help develop more targeted policy tools in response to banking sector risks.

5 Conclusion

We develop a novel measure of bank solvency — economic capital (EC) — that jointly quantifies credit, liquidity, and market risk using publicly available regulatory data. By valuing both assets and liabilities at present value and stressing depositor behavior, our framework provides an internally consistent assessment of bank health across multiple scenarios spanning nearly three decades of banking history.

Using economic capital, we are able to glean useful insights about vulnerabilities at individual banks and the banking sector more broadly. Economic capital substantially outperforms conventional capital metrics in predicting bank failures at long horizons. Our measure reveals vulnerabilities obscured by traditional metrics: banking sector capital has improved less since the Global Financial Crisis than regulatory ratios suggest, largely due to significant variation in the value of deposit funding. We show that through the lens of economic capital, the 2023 banking turmoil was predictable years in advance, while book capital deteriorated only immediately before failure. System-wide interest rate risk remains elevated despite peaking in 2022.

Beyond identifying systemic vulnerabilities, our transparent framework enables practical applications for policymakers and researchers. We demonstrate how economic capital can evaluate stabilization policies like the Bank Term Funding Program, assess the relationship between bank health and credit supply, and inform forward-looking financial stability analysis. The framework's flexibility allows for scenario analysis and stress testing that captures the complex interactions between funding liquidity, asset quality, and market conditions —- providing a rich toolkit for understanding and managing banking sector risks. While greater granularity in regulatory data on hedges, loan portfolios, and deposit characteristics would enhance precision, our current measure offers substantial predictive and analytical power for assessing banking sector health.

References

Adrian, T., R. K. Crump, and E. Moench (2013): "Pricing the term structure with linear regressions," *Journal of Financial Economics*, 110, 110–138.

Ashcraft, A. B. (2005): "Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks," *American Economic Review*, 95, 1712–1730.

Basel Committee on Banking Supervision (2015): "Interest rate risk in the banking book," Website link.

Begenau, J., M. Piazzesi, and M. Schneider (2015): "Banks' risk exposures," *NBER Working Paper*.

Bernanke, B. S. (2023): "Nobel Lecture: Banking, Credit, and Economic Fluctuations," *American Economic Review*, 113, 1143–69.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2024): "The secular decline of bank balance sheet lending," *NBER Working Paper*.

Cattaneo, M. D., R. K. Crump, M. H. Farrell, and Y. Feng (2024): "On Binscatter," *American Economic Review*, 114, 1488–1514.

Chodorow-Reich, G. (2014): "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-09 Financial Crisis," *Quarterly Journal of Economics*, 129, 1–59, ¡p¿Lead article¡/p¿.

Chodorow-Reich, G., O. Darmouni, S. Luck, and M. Plosser (2022): "Bank liquidity provision across the firm size distribution," *Journal of Financial Economics*, 144, 908–932.

Cole, R. A. and J. W. Gunther (1998): "Predicting bank failures: A comparison of on-and off-site monitoring systems," *Journal of Financial Services Research*, 13, 103–117.

Corbae, D. and P. D'Erasmo (2021): "Capital Buffers in a Quantitative Model of Banking Industry Dynamics," *Econometrica*, 89, 2975–3023.

Correia, S., S. Luck, and E. Verner (2025): "Failing Banks*," *The Quarterly Journal of Economics*, qjaf044.

Curti, F. and J. R. Gerlach (2024): "A Framework for Evaluating Banks' Resilience in a Rising Interest Rate Environment," *Available at SSRN*.

DeMarzo, P., A. Krishnamurthy, and S. Nagel (2024): "Interest Rate Risk in Banking," *Working paper*.

Diamond, D. W. and P. H. Dybvig (1983): "Bank Runs, Deposit Insurance, and Liquidity," *Journal of Political Economy*, 91, 401–419.

Diebold, F. X. and S. A. Sharpe (1990): "Post-Deregulation Bank-Deposit-Rate Pricing: The Multivariate Dynamics," *Journal of Business & Economic Statistics*, 8, 281–291.

Drechsler, I., A. Savov, and P. Schnabl (2017): "The deposits channel of monetary policy," *The Quarterly Journal of Economics*, 132, 1819–1876.

——— (2021): "Banking on deposits: Maturity transformation without interest rate risk," *The Journal of Finance*, 76, 1091–1143.

Drechsler, I., A. Savov, P. Schnabl, and O. Wang (2023): "Banking on uninsured deposits," *Available at SSRN 4411127*.

Egan, M., A. Hortaçsu, and G. Matvos (2017): "Deposit Competition and Financial Fragility: Evidence from the US Banking Sector," *American Economic Review*, 107, 169–216.

Egan, M., S. Lewellen, and A. Sunderam (2021): "The Cross-Section of Bank Value," *The Review of Financial Studies*, 35, 2101–2143.

Emin, M., C. James, and T. Li (2023): "Variable Deposit Betas and Bank Interest Rate Risk Exposure," *Available at SSRN 4411127*.

English, W. B., S. J. Van den Heuvel, and E. Zakrajšek (2018): "Interest rate risk and bank equity valuations," *Journal of Monetary Economics*, 98, 80–97.

Federal Deposit Insurance Corporation (2023): "Formal and informal enforcement actions manual," Website link.

Flannery, M. J. (1981): "Market Interest Rates and Commercial Bank Profitability: An Empirical Investigation," *The Journal of Finance*, 36, 1085–1101.

Flannery, M. J. and C. M. James (1984): "Market evidence on the effective maturity of bank assets and liabilities," *Journal of Money, Credit and Banking*, 16, 435–445.

Flannery, M. J. and S. M. Sorescu (2023): "Partial effects of fed tightening on us banks' capital," *Working paper*.

Fleckenstein, M. and F. A. Longstaff (2024): "Is Maturity-Transformation Risk Priced into Bank Deposit Rates?" Working Paper 32724, NBER.

Fuster, A. and J. I. Vickery (2018): "Regulation and risk shuffling in bank securities portfolios," *FRB of New York Staff Report*.

Goldstein, I. and A. Pauzner (2005): "Demand–deposit contracts and the probability of bank runs," *the Journal of Finance*, 60, 1293–1327.

Gomez, M., A. Landier, D. Sraer, and D. Thesmar (2021): "Banks' exposure to interest rate risk and the transmission of monetary policy," *Journal of Monetary Economics*, 117, 543–570.

Granja, J., E. X. Jiang, G. Matvos, T. Piskorski, and A. Seru (2024): "Book value risk management of banks: Limited hedging, HTM accounting, and rising interest rates," *NBER Working Paper*.

Greenwald, E., S. Schulhofer-Wohl, and J. Younger (2023): "Deposit Convexity, Monetary Policy and Financial Stability," .

Gürkaynak, R. S., B. Sack, and J. H. Wright (2007): "The US Treasury yield curve: 1961 to the present," *Journal of monetary Economics*, 54, 2291–2304.

Haddad, V., B. Hartman-Glaser, and T. Muir (2023): "Bank fragility when depositors are the asset," *Available at SSRN 4412256*.

Hannan, T. H. and A. N. Berger (1991): "The Rigidity of Prices: Evidence from the Banking Industry," *The American Economic Review*, 81, 938–945.

Hanson, S. G. (2014): "Mortgage Convexity," *Journal of Financial Economics*, 113, 270–299.

Hanson, S. G., A. K. Kashyap, and J. C. Stein (2011): "A Macroprudential Approach to Financial Regulation," *Journal of Economic Perspectives*, 25, 3–28.

Hanson, S. G., A. Shleifer, J. C. Stein, and R. W. Vishny (2015): "Banks as patient fixed-income investors," *Journal of Financial Economics*, 117, 449–469.

Haughwout, A., D. Lee, D. Mangrum, J. W. Scally, and W. van der Klaauw (2024): "Mortgage Lock In Spurs Recent HELOC Demand," Liberty Street Economics Blog; August 6.

Hughes, J. P. and L. J. Mester (2013): "Who said large banks don't experience scale economies? Evidence from a risk-return-driven cost function," *Journal of Financial Intermediation*, 22, 559–585.

Hutchison, D. E. and G. G. Pennacchi (1996): "Measuring Rents and Interest Rate Risk in Imperfect Financial Markets: The Case of Retail Bank Deposits," *Journal of Financial and Quantitative Analysis*, 31, 399–417.

Iyer, R. and M. Puri (2012): "Understanding Bank Runs: The Importance of Depositor-Bank Relationships and Networks," *American Economic Review*, 102, 1414–45.

Jiang, E. X., G. Matvos, T. Piskorski, and A. Seru (2024): "Monetary tightening and U.S. bank fragility in 2023: Mark-to-market losses and uninsured depositor runs?" *Journal of Financial Economics*, 159, 103899.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2012): "Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications," *American Economic Review*, 102, 2301–26.

Kang-Landsberg, A., S. Luck, and M. Plosser (2023): "Deposit Betas: Up, Up, and Away?" Liberty Street Economics Blog; April 11, 2023.

Kashyap, A. K., R. Rajan, and J. C. Stein (2002): "Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-taking," *The Journal of Finance*, 57, 33–73.

Khwaja, A. I. and A. Mian (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 98, 1413–42.

Luck, S., M. Plosser, and J. Younger (2023): "How Do Interest Rates (and Depositors) Impact Measures of Bank Value?" Liberty Street Economics Blog; April 10, 2023.

McPhail, L., P. Schnabl, and B. Tuckman (2023): "Do Banks Hedge Using Interest Rate Swaps?" .

Modigliani, F. and M. H. Miller (1958): "The cost of capital, corporation finance and the theory of investment," *The American economic review*, 48, 261–297.

Mullineaux, D. J. (1978): "Economies of Scale and Organizational Efficiency in Banking: A Profit- Function Approach," *The Journal of Finance*, 33, 259–280.

Myers, S. C. (1977): "Determinants of corporate borrowing," *Journal of Financial Economics*, 5, 147–175.

Myers, S. C. and N. S. Majluf (1984): "Corporate financing and investment decisions when firms have information that investors do not have," *Journal of Financial Economics*, 13, 187–221.

Office of the Comptroller of the Currency (2024): "Interest Rate Risk Statistics Report," Website link.

Peek, J. and E. S. Rosengren (1997): "The International Transmission of Financial Shocks: The Case of Japan," *The American Economic Review*, 87, 495–505.

Plosser, M. C. and J. A. C. Santos (2023): "The Cost of Bank Regulatory Capital," *The Review of Financial Studies*, 37, 685–726.

Samuelson, P. A. (1945): "The Effect of Interest Rate Increases on the Banking System," *The American Economic Review*, 35, 16–27.

Schwert, M. (2020): "Does borrowing from banks cost more than borrowing from the market?" *The Journal of Finance*, 75, 905–947.

Sherman, R. G. (2013): "Valuing Core Deposits," *Journal of Financial Services Research*, 43, 197–220.

S&P Global (2023): "Number of US banks with negative adjusted tangible common equity nearly doubles," Website link.

van Binsbergen, J. H. and R. S. Koijen (2017): "The term structure of returns: Facts and theory," *Journal of Financial Economics*, 124, 1–21.

Van den Heuvel, S. (2024): "The welfare effects of bank liquidity and capital requirements," *FEDS Working Paper*, 2022.

Wheelock, D. C. and P. W. Wilson (2012): "Do Large Banks Have Lower Costs? New Estimates of Returns to Scale for U.S. Banks," *Journal of Money, Credit and Banking*, 44, 171–199.

Internet Appendix for "Bank Economic Capital"

Beverly Hirtle Matthew C. Plosser*

The Internet Appendix contains supplementary materials for the article "Bank Economic Capital." Section A presents the definitions for the variables and data sources. Sections B, C, and D contain details and supporting evidence for our calculation of present values for fixed rate portfolios, demand deposits, and expenses, respectively.

*Citation format: Hirtle, Beverly and Matthew C. Plosser, Internet Appendix for "Bank economic capital."

A Data

A.1 Balance sheet

Our primary source of data is the Call Report. The tables below summarize the variables and their construction.

Table IA1: Balance sheet variables: Assets. Call Report fields. Mnemonics may need to be adjusted for domestic only firms and historical changes in reporting. Stated ranges are inclusive.

Variable	Mnemonic	Field	Valid Period
Par/Fair Value:			
Interest bearing balances	RCFD	0071	$\geq$ 1984:Q1
Noninterest bearing balances	RCFD	0081	$\geq$ 1984:Q1
Federal funds sold and reverse repo	RCFD	1350	$\geq$ 1969:Q2
		B987+B989	$\geq$ 2002:Q1
Available for sale (AFS) securities	RCFD	1773	$\geq$ 1994:Q1
Equity securities at fair value	RCFD	A511	1997:Q1 - 2017:Q4
		JA22	$\geq$ 2018:Q1 $\vee$ $\geq$ 2020:Q1
Loans and leases, Held For Sale (HFS)	RCFD	5369	$\geq$ 1997:Q1
Trading assets	RCFD	3545	$\geq$ 1993:Q4
Other fair value items		B556+HT80	$\geq$ 2001:Q1
Amortized Cost:			
Held to maturity (HTM) securities	RCFD	1754	$\geq$ 1994:Q1
Mortgage servicing rights (MSR)	RCFD	3164	$\geq$ 2001:Q1
Premises and fixed assets	RCFD	2145	$\geq$ 1969:Q2
Intangible assets	RCFD	2143	$\geq$ 1983:Q1
Other (Residual w/ total assets)			
Held for investment, loans and leases	RCFD	2122 - 5369	1991:Q1 - 2000:Q4
		B528	$\geq$ 2001:Q1
Allowance for loan losses	RCFD	3123	$\geq$ 1976:Q1
Total assets	RCFD	2170	$\geq$ 1969:Q2
Fair Values Reported Elsewhere:			
Held to maturity (HTM) securities	RCFD	1771	$\geq$ 1994:Q1
Mortgage servicing rights (MSR)	RCFD	A590	$\geq$ 2001:Q1

Table IA2: Balance sheet variables: Liabilities. Call Report fields. Mnemonics may need to be adjusted for domestic only firms and historical changes in reporting

Variable	Mnemonic	Field	Valid Period
Par/Fair Value:			
Federal funds purchased and repo	RCFD	2800	$\geq$ 1969:Q2
		B993+B995	$\geq$ 2002:Q1
Trading liabilities	RCFD	3548	$\geq$ 1994:Q1
Other fair value items	RCFD	3049	$\geq$ 1984:Q1
Amortized Cost:			
Other book value items	RCFD	2930 - 3049	$\geq$ 1990:Q1
Subordinated debt	RCFD	3200	$\geq$ 1969:Q2
Other borrowed money	RCFD	2332+2333	1997:Q1
		2332+A547+A548	1997:Q2 - 2000:Q4
		3190	$\geq$ 2001:Q1
Time deposits	RCON	6648 + 2604	1984:Q1 - 2009:Q4
		6648+J473+J474	$\geq$ 2010:Q1
Domestic demand deposits	RCON	6631+6636-Time dep.	$\geq$ 1984:Q1
Foreign demand deposits	RCFN	6631+6636	$\geq$ 1984:Q1
Equity (incl. minority int.)	RCFD	G105	$\geq$ 2009:Q1
		3210+3000	1969:Q2 - 2008:Q4

A.2 Discount rates

Table IA3: Discount rates. Variables and sources.

Variable	**Source**	**FRED variable / Source link**	**Valid Period**
GSW constant-maturity yields	FR Board	Source link	$\geq$ 1961
ACM risk-neutral yields	FR Bank of NY	Source link	$\geq$ 1961
Corporate OAS spreads:			
AAA	ICE BofA Index (FRED)	BAMLC0A1CAAA	$\geq$ 1997
Single-A	ICE BofA Index (FRED)	BAMLC0A3CA	$\geq$ 1997
BBB	ICE BofA Index (FRED)	BAMLC0A4CBBB	$\geq$ 1997
BB	ICE BofA Index (FRED)	BAMLH0A1HYBB	$\geq$ 1997
Single-B	ICE BofA Index (FRED)	BAMLH0A2HYB	$\geq$ 1997
Corporate credit curve	U.S. Treasury	Source link	$\geq$ 1984

B Fixed rate portfolios

This section outlines the technical details for the calculation of fixed rate portfolio present values (Section 3.2).

B.1 Maturity schedules

Figure IA1. Call Report Schedule RC-C Loans: Maturity.

Schedule RC-C—Continued

Dollar Amounts in Thousands	RCON	Amount	
2. Maturity and repricing data for loans and leases (excluding those in nonaccrual status):			
a. Closed-end loans secured by first liens on 1–4 family residential properties in domestic offices (reported in Schedule RC-C, Part I, item 1.c.(2)(a), column B) with a remaining maturity or next repricing date of:[1,2]			
(1) Three months or less	A564		M.2.a.(1)
(2) Over three months through 12 months	A565		M.2.a.(2)
(3) Over one year through three years	A566		M.2.a.(3)
(4) Over three years through five years	A567		M.2.a.(4)
(5) Over five years through 15 years	A568		M.2.a.(5)
(6) Over 15 years	A569		M.2.a.(6)
b. All loans and leases (reported in Schedule RC-C, Part I, items 1 through 10, column A) EXCLUDING closed-end loans secured by first liens on 1–4 family residential properties in domestic offices (reported in Schedule RC-C, Part I, item 1.c.(2)(a), column B) with a remaining maturity or next repricing date of:[1,3]	RCFD		
(1) Three months or less	A570		M.2.b.(1)
(2) Over three months through 12 months	A571		M.2.b.(2)
(3) Over one year through three years	A572		M.2.b.(3)
(4) Over three years through five years	A573		M.2.b.(4)
(5) Over five years through 15 years	A574		M.2.b.(5)
(6) Over 15 years	A575		M.2.b.(6)

Figure IA2. Call Report Schedule RC-E Time Deposits: Maturity Schedule.

Schedule RC-E—Continued

Memoranda—Continued

Dollar Amounts in Thousands	RCON	Amount	
3. Maturity and repricing data for time deposits of $250,000 or less:			
a. Time deposits of $250,000 or less with a remaining maturity or next repricing date of:[1,2]			
(1) Three months or less	HK07		M.3.a.(1)
(2) Over three months through 12 months	HK08		M.3.a.(2)
(3) Over one year through three years	HK09		M.3.a.(3)
(4) Over three years	HK10		M.3.a.(4)

Figure IA3. Call Report Schedule RC-M Other Borrowed Money.

Schedule RC-M—Memoranda

Dollar Amounts in Thousands	RCFD	Amount	
5. Other borrowed money:			
a. Federal Home Loan Bank advances:			
(1) Advances with a remaining maturity or next repricing date of:[2]			
(a) One year or less	F055		5.a.(1)(a)
(b) Over one year through three years	F056		5.a.(1)(b)
(c) Over three years through five years	F057		5.a.(1)(c)
(d) Over five years	F058		5.a.(1)(d)
(2) Advances with a REMAINING MATURITY of one year or less (included in item 5.a.(1)(a) above)[3]	2651		5.a.(2)
(3) Structured advances (included in items 5.a.(1)(a) - (d) above)	F059		5.a.(3)
b. Other borrowings:			
(1) Other borrowings with a remaining maturity or next repricing date of:[4]			
(a) One year or less	F060		5.b.(1)(a)
(b) Over one year through three years	F061		5.b.(1)(b)
(c) Over three years through five years	F062		5.b.(1)(c)
(d) Over five years	F063		5.b.(1)(d)
(2) Other borrowings with a REMAINING MATURITY of one year or less (included in item 5.b.(1)(a) above)[5]	B571		5.b.(2)
c. Total (sum of items 5.a.(1)(a)-(d) and items 5.b.(1)(a)-(d)) (must equal Schedule RC, item 16)	3190		5.c.

Figure IA4. Call Report Schedule RC-O Subordinated Debt Maturity Schedule.

Schedule RC-O—Other Data for Deposit Insurance Assessments

8. Subordinated notes and debentures with a remaining maturity of (sum of items 8.a through 8.d must equal Schedule RC, item 19):			
a. One year or less	G469		8.a.
b. Over one year through three years	G470		8.b.
c. Over three years through five years	G471		8.c.
d. Over five years	G472		8.d.

B.2 Time-to-maturity buckets (m)

To capture the natural maturation of instruments over time, we assign the reported maturity categories shown in Section B.1 to specific quarters reflecting time-to-maturity. To do so, we uniformly distribute the book value of loans within a maturity category to a specific quarterly horizon. Table IA4 outlines the range of maturities assigned to each instrument category.

Table IA4: Quarter-to-maturity ranges. To track the evolution of instruments in the reported maturity schedules over time, we assign them to specific time-to-maturity buckets where time-to-maturity is measured in quarters. The ranges used for each instrument maturity schedule are described below. Book values are uniformly distributed across quarters within these ranges (inclusive).

	Quarters-to-maturity			**Quarters-to-maturity**	
Assets	**Minimum**	**Maximum**	**Liabilities**	**Minimum**	**Maximum**
Loans:			**Non-deposit:**		
$\leq$ 3 months	1	1	$\leq$ 1 year	1	4
3 - 12 months	2	4	1 - 3 years	5	12
1 - 3 years	5	12	3 - 5 years	13	20
3 - 5 years	13	20	$>$ 5 years	21	40
5 - 15 years	21	60	**Time deposits:**		
$>$ 15 years:			$\leq$ 3 months	1	1
Residential RE	61	120	3 - 12 months	2	4
All other	61	80	1 - 3 years	5	12
			$>$ 3 years	13	20

B.2.1 Held-for-sale loans

One nuance to this process is that the loan maturity schedules in the Call Report (Fig. IA1 include held-for-sale (HFS) loans.[1] These loans are already booked at their fair value so we would like to remove them from them from the reported quantities before we apply our fixed-rate portfolio methodology for estimating present values and then add them back once we have estimated present values.

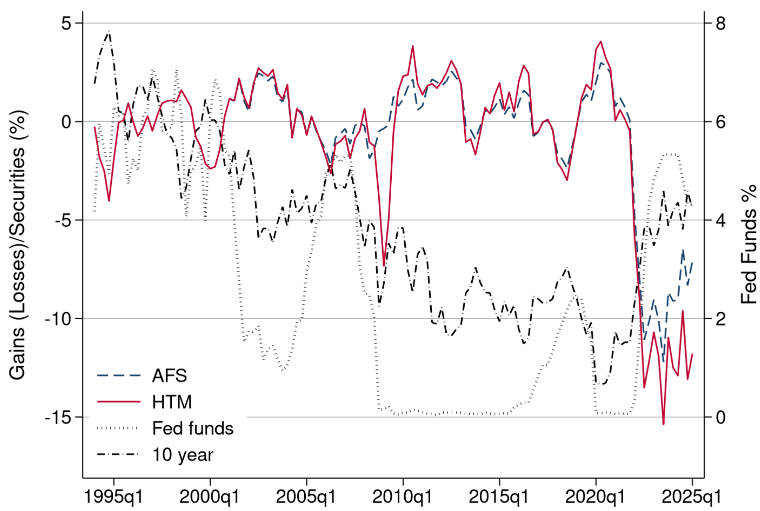
We ideally can identify the 1-4 family mortgage loans HFS and all other loans. There are two potential sources of information for the former that allow us to identify the mix of HFS loans. The first is in Call Report Schedule RC-P, line 4, which reports 1-4 family residential mortgages held for sale or trading. The second is in Schedule RC-Q, line 3, which reports loans measured at fair value. Each has limitations. The former is only completed for banks where loans held for sale exceed \$10m for two consecutive quarters. In addition, it includes

[1] The instructions for Schedule RC-C state: "Do not deduct the allowance for loan and lease losses or the allocated transfer risk reserve from amounts reported in this schedule. Report (1) loans and leases held for sale at the lower of cost or fair value, (2) loans and leases held for investment, net of unearned income, and (3) loans and leases accounted for at fair value under a fair value option."

loans held in the trading book (< 3% of bank-quarters report trading assets greater than zero). The latter are completed by banks that have either elected to book loans at fair value or have more than $10m in trading assets or liabilities for two consecutive quarters.

We can use these fields to generate an estimate of the total loans held for sale in the two categories of loans: 1-4 family residential mortgages and other loans. Schedule RC-Q, line 3.a.1 reports the loans measured at fair value secured by 1-4 family property loans and the sum of lines 3.b-3.d. report the value of all other loans reported at fair value.

Figure IA5. Securities portfolio market value relative to carrying value: AFS and HTM. This figure plots aggregate mark-to-market gains/(losses) relative to the amortized cost of securities. The figure does this separately for HTM and AFS securities. The figure also includes the variation in the fed funds rate and 10-year treasury rate.



We distribute these allocations into maturity categories using the historical tendencies of the securities portfolios and conservatism as a guide. Empirically, the relative mark-to-market gains/(losses) of AFS securities portfolios tend to be smaller than the those of HTM portfolios, as evidenced by Figure IA5 where AFS experience less distress during the GFC or the recent rate hiking cycle. And, HTM market values are more persistent and more sensitive to changes in longer maturities, like the two- and ten-year yield, whereas AFS securities are more sensitive to short rates, like the fed funds rate (see Table IA5). Hence, the evidence suggests that HTM portfolios on average contain longer-maturity securities than AFS portfolios — a finding that is consistent with banks seeking to minimize exposure to interest rate risk in reported earnings (Fuster and Vickery, 2018). Moreover, attributing shorter-maturities to AFS and HFS loans is conservative as it minimizes the attenuation of portfolio durations and maximizes sensitivity to interest rates.

With these factors as motivation, we implement an allocation "waterfall", whereby the fair value of HFI loans are assigned to ascending maturity buckets. When a maturity bucket is fully accounted for, the remaining HFS value is assigned to the next highest bucket and so on. What remains in the maturity distribution is then ascribed to the amortized cost of HFI

Table IA5: Sensitivity of AFS and HTM losses to interest rates. This table reports estimates from the regression of the ratio of MTM gains/(losses) to the carrying value of the securities portfolio on the lagged ratio and contemporaneous changes in interest rates. Columns 1 and 3 consider HTM securities, columns 2 and 4 AFS securities. Regressions are weighted by portfolio size. Interest rates are the fed funds and the 10-year constant maturity Treasury rate. Standard errors reported in parentheses are clustered by bank and date. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) HTM	(2) AFS	(3) HTM	(4) AFS
Δ Fed funds	0.03	-2.72***	0.12	-3.40**
	(0.27)	(1.02)	(0.36)	(1.36)
Δ 10-year	-3.79***	-1.35	-4.11***	-0.97
	(0.48)	(1.08)	(0.50)	(1.45)
Lag HTM Gains/Sec.	0.96***		0.96***	
	(0.02)		(0.02)	
Lag AFS Gains/Sec.		0.01		0.00
		(0.00)		(0.00)
Constant	-0.32***	-1.17***	-0.32**	-1.56***
	(0.11)	(0.43)	(0.13)	(0.51)
Observations	443699	573997	159721	390155
Adj. R^2	0.95	0.08	0.95	0.11
Period	Full	Full	>2007:Q2	>2007:Q2
Weighted?	Yes	Yes	Yes	Yes
Y mean	-4.40	-1.33	-4.97	-1.76

loans. This process is repeated for both loan categories. Table IA6 summarizes the process for categories with seven maturity buckets.

Table IA6: Maturity waterfall for assigning HFS loans to maturity categories. M_i are the reported values from RC-C (Fig. IA1). Total HFS loans, A, is based on the proportional assignment of the related categories on Call Report schedule RC-B. AFS assignments are at fair value and HTM at amortized cost. A_j and H_k are calculated according to the equations in the table. The average maturity of each bucket is indicated in the second column and is used to compute sensitivity to interest rates.

Time-to-Maturity	**Reported**	**Assigned**	
Category	**Value**	**HFS FV**	**HFI AC**
$\leq$ 3 months	M_0	$A_0 = \min(M_0, A)$	$H_0 = M_0 - A_0$
3 - 12 months	M_1	$A_1 = \min(M_1, A - A_1)$	$H_1 = M_1 - A_1$
1 - 3 years	M_2	$A_1 = \min(M_1, A - \sum_j^2 A_j)$	$H_2 = M_2 - A_2$
3 - 5 years	M_3	$A_1 = \min(M_1, A - \sum_j^3 A_j)$	$H_3 = M_3 - A_3$
5 - 15 years	M_4	$A_1 = \min(M_1, A - \sum_j^4 A_j)$	$H_4 = M_4 - A_4$
> 15 years	M_5	$A_1 = \min(M_1, A - \sum_j^5 A_j)$	$H_5 = M_5 - A_5$

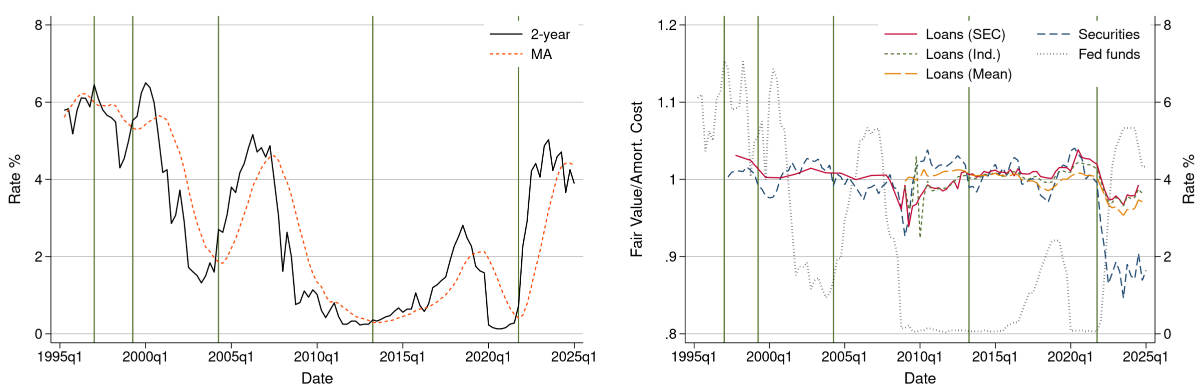
B.3 Initial values (PV_0)

As described in Section 3.2, our approach to estimating the value of fixed-rate portfolios requires an initial present value (PV_0) with which to calculate future changes. The Call Report does not report the present (e.g., fair, market) values of these loans; therefore, we must assume the fair value at a point in time.

Empirically, the present value of fixed rate securities portfolios reverts to book value over rate cycles: fair values exceed book when risk-free rates fall and lag book as interest rates rise. In a sub-sample of hand-collected loan fair values obtained from SEC filings, we find a similar reversion pattern towards equality. The reversion is consistent with the oscillation of discount rates and the incentive for borrowers to refinance fixed rate loans that are greater than book value.

Figure IA6. Initial Present Value Dates (PV_0). This figure contains plots that indicate the dates where we assume the present value is the same as the book value (vertical green lines). Figure IA6a illustrates how we select the dates by depicting the two-year constant-maturity yield and its two-year moving average. PV_0 dates are those dates where the yield exceeds the moving average for at least two quarters for the first time in a year. Figure IA6b illustrates the relative fair value to amortized cost for *Securities* (weighted average from Call Report), *Loans (SEC)* (weighted average from 13 banks' SEC filings), *Loans (Ind.)* (weighted average from CapIQ/SNL), and *Loans (Mean)* (simple average from CapIQ/SNL). Loan samples are not available for the entire sample history

(a) PV_0 date selection   **(b)** FV/AC



With these two forces in mind, we adopt a parsimonious measure of rate cycles using the current two-year yield relative its two-year moving average. If the current rate exceeds the moving average for the first time in a year and stays there for two quarters, we define the first quarter as the start of a new credit cycle (i.e., $t = 0$).[2] Table IA7 summarizes the PV_0 dates and shows the fair value-to-book value for securities and several sub-samples of loans. Importantly the two values are close to one at these dates, supporting our assumption that present values are similar to book values at these inflection points in the rate cycle.

At each of these cycle start dates, we assume that the present value of fixed rate instruments are equal to the book value. We then calculate changes in present value using Equation 2 and the parameter values below. Banks that enter between cycle starts are assigned

[2] Similar cycle dates are obtained for most maturities even if we exclude the two quarter restriction. We obtain the same dates if we use the three-year yield. There are minor differences for the five- and one-year maturities that do not materially impact our value calculations.

Table IA7: PV_0 **dates and FV/AC ratios**. This table reports the dates at which we assume the present value of fixed-rate portfolios are the same as book values. For these dates, we also report the fair value-to-book value for *Securities* (weighted average from Call Report), *Loans (SEC)* (weighted average from 13 banks' SEC filings), *Loans (Ind.)* (weighted average from CapIQ/SNL), and *Loans (Mean)* (simple average from CapIQ/SNL). Loan samples are not available for the entire sample history.

	FV/AC			
	Securities	Loans (SEC)	Loans (Ind.)	Loans (Mean)
1997q1	1.00			
1999q2	0.99	1.01		
2004q2	0.99	1.01		
2013q2	0.99	1.01	1.00	1.01
2021q4	1.00	1.02	1.01	1.00

a present value for each instrument and maturity that is consistent with the corresponding ratio of present value to book value for the industry.

B.4 Originations

New originations are estimated by first rolling-forward the book value of a one-quarter higher maturity bucket in the prior quarter, BV_{t-1}^{m+1}, which provides a 'projected' book value for each maturity bucket. Then, we reduce this value by the proportion prepaid, pp_t, and subtract the actual value of the maturity bucket in the current quarter, BV_t^m.

$$O_t^m = \max(BV_t^m - (1 - pp_t)BV_{t-1}^{m+1}, 0) \tag{7}$$

If the actual book value at time t exceeds the projected value from $t-1$, we assume the excess are new originations recorded at fair value, O_t^m; otherwise, we assume originations are zero. Assuming the book value of new originations is equal to their fair value effectively assumes that new loans are issued at par.

In the event that actual book value for a maturity bucket is *smaller* than our projection, originations are set to zero for that bucket and we define a scaling factor for that bucket of loans that implies a higher prepayment rate.

$$pp_t^m = \min(1 - pp_t, \frac{BV_t^m}{BV_{t-1}^{m+1}}) \tag{8}$$

In other words, if the book value for a bucket declines by more than our modelled prepayment rate we reflect this in our present value calculation by assuming higher prepayment for that bank and that maturity.

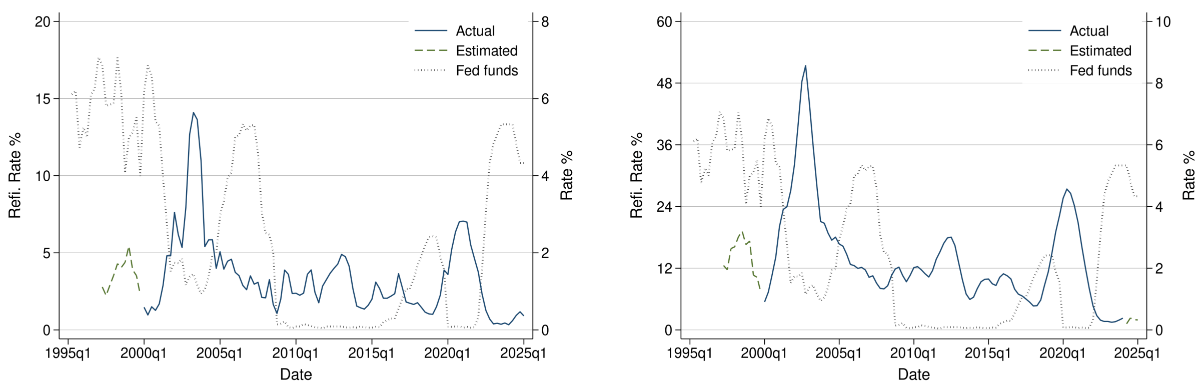
B.5 Prepayment

An important feature of loans, particularly longer dated loans like mortgages, is prepayment. If loans are typically prepaid before their contractual maturity date it impacts the evolution of portfolio maturity and new originations, Eq. 7. In addition, prepayment expectations reduce the effective maturity of a loan and therefore its duration.

To estimate the prepayment rate for residential mortgages, pp_t, we use data from the NY Fed/Equifax Consumer Credit Panel. The panel contains a representative 5% sample of U.S. households for the period 2000 through 2024. Mortgage information in the sample allows us to calculate the refinance rate of outstanding mortgages, which we use as a proxy for the prepayment rate of mortgages.[3] Figure IA7a illustrates quarterly mortgage refinance rates from 1997 through 2023. The actual refinance rates are only available from 2001:Q1 onward; therefore, we estimate refinance rates for the three years from 1997 to 2000 using a linear regression. We regress the log of refinance rates on the average 30-year mortgage rate less its six-year minimum. The coefficient is negative and statistically significant which is consistent with falling rates increasing refinancing activity.[4]

Figure IA7. Residential real estate refinance rates. This figure contains plots of mortgage refinance rates obtained from the NY Fed/Equifax CCP. Figure IA7a depicts actual quarterly refinance rates for the period 2000-2023 and fills in estimated rates for the period 1997-1999. Estimated rates are calculated using a linear regression of actual log refinance rates on average 30-year mortgage rates less their six-year minimum. Figure IA7b depicts actual one-year forward refinance rates for the period 2000-2022 and projected rates for 1997-1998 and 2023 to 2024:Q1. Projected rates are estimated using a linear regression of log 1-year forward refinance rates on the current refinance rate, the 30-year yield less its three-year moving average, the mortgage spread less its three-year moving average, and the five-year yield less its one year moving average.

(a) Quarterly **(b)** 1-Year Forward



In addition to the refinance rate, we also add the contractual paydown of mortgages where the annualized paydown for each maturity bucket is a function of time-to-maturity

[3]Thanks to Donghoon Lee for providing these estimates. See Haughwout et al. (2024) for applications of this work.

[4]The precise regression estimates are

$$\log(Rate_t) = -3.12 - 0.67Y^{Mtg}_{t-2},$$

where Y^{Mtg} is the 30-year mortgage rate reported by Freddie Mac less its six-year minimum. The R-squared from this regression is 66%.

$(4/m)$ — loans closer to maturity reduce their principal at a faster rate. We only assume 70% of on-balance sheet residential real estate loans behave this way (consistent with the mix of amortizing loans as estimated using FR Y-14 data).

To incorporate prepayment into our estimates of duration, we use a modified version of Equation 3 that includes an expected prepayment rate, δ,

$$D = \frac{\partial p}{\partial y}\frac{1}{p} = \frac{1}{p}\frac{1}{y+\delta}\left[1 - \frac{(1-\delta/f)^{fm}}{(1+y/f)^{fm}}\right]. \tag{9}$$

To obtain expected prepayment, we use the quarterly series to calculate a cumulative one-year forward refinance rate. For the period prior to 2000 this rate includes estimated rates as described above. For the year 2023 we estimate refinance rates as a function of lagged refinance rates and yields to project annual rates. The result of this process is shown in Figure IA7b.[5] We use these time-varying estimates of δ in Equation 9 along with the contractual pay-down rate to calculate RRE durations for the range of maturity buckets over one year.

For all other loans, we apply a simple rule that assumes a prepayment rate that ranges from 5% to 25% depending on the level of the BBB yield relative to its four-year moving average. If the two-quarter moving average (MA) exceeds the five year minimum by more than 50bps, we assume prepayment is at its lower bound, 5%. If the two-quarter MA is 100bps less than the four-year moving, we assume that prepayment is 25%. Between these bounds we interpolate prepayment rates based on the the difference between the two moving averages. See Figure IA8 for a depiction of these time periods. As rates rise, prepayment decreases and the duration of the portfolio rises. As rates fall, prepayment increases and the duration of the portfolio declines.

B.6 Discount rates

Risk-free rates, rf_t: For the risk-free component of discount rates, we calculate a rate for each quarter-to-maturity horizon m based on constant-maturity par yields.

$$rf_t^m = (1 + rf_t^a)^a (1 + f_t^{a\to a+1})^{\frac{m-4a}{4}} - 1, \tag{10}$$

where rf^a is the largest annual yield before m and $f_t^{a\to a+1}$ is the implied annual forward rate for maturity between a and the next available yield. For example, the rate for a 28 quarter (7 year) maturity bucket is given by the 5-year yield and a forward rate for the period from 5 to 10 years:

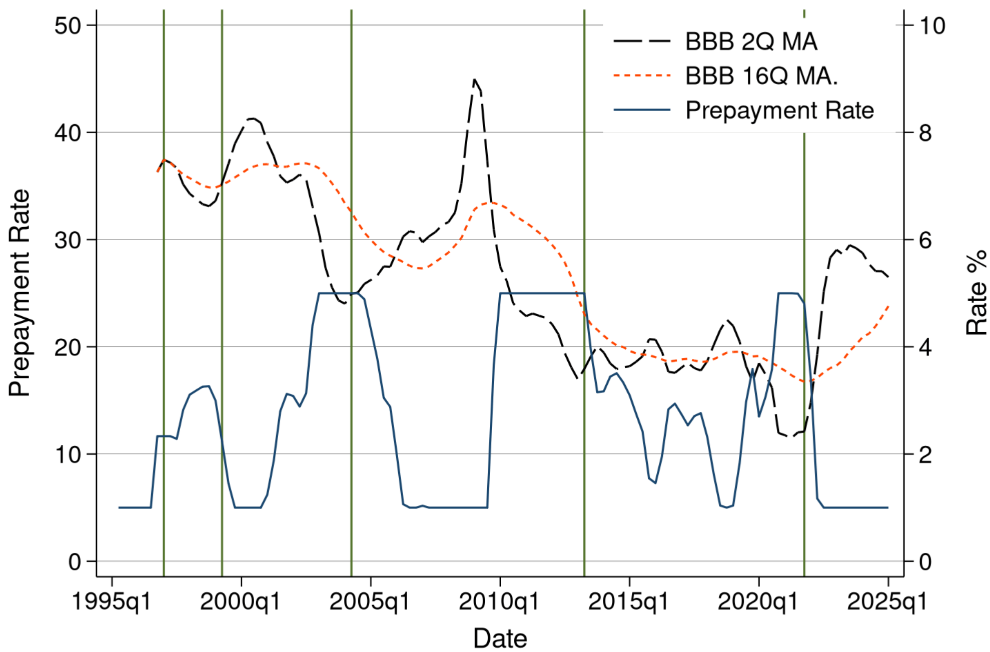
$$rf_t^{28} = (1 + rf_t^5)^5 (1 + f_t^{5\to 10})^2 - 1. \tag{11}$$

[5] We project 1-year forward refinance rates for the end of the sample period using the following regression,

$$\log\left(Rate_{t+1\to t+4}^{1y}\right) = -0.65 + 0.54\log(Rate_t) - 0.20\log(Rate_{t-1}) - 0.4Y_t^{Mtg}.$$

The R-squared of this regression is 80% and the variable coefficients are all statistically significant at the 5% level. Y^{Mtg} is the 30-year mortgage rate reported by Fannie Mae less its six-year minimum.

Figure IA8. All other prepayment periods. This figure plots the estimated prepayment rates for all other loans. Rates are bounded between 5% and 25% based on the level of the BBB corporate yield. If the two-quarter MA is greater than the eight-quarter minimum by more than 35bps prepayments are set at 5%. If the difference is less than 0 the difference is set at 25%. Between these two differences we interpolate the prepayment rate from 5% to 30%.



B.6.1 Heterogeneous risk premia

To obtain bank-specific risk premia for loan discount rates, we use loan interest income to infer the relative riskiness of the portfolio. We assign a risk premium that ranges from the corporate AA spread to the average of the corporate single-B and BB spreads (BB-B). Then, we apply the corporate credit curve to adjust the assigned spread to specific maturities. Our use of corporate spreads for all loans is based on data availability throughout our sample period. Conceptually, a similar exercise could be done using indices that reflect specific loan types.

Loan rates: We first calculate the implicit annual interest rate on loans using quarterly interest income on loans for each bank i and each quarter t divided by the average loan balance between the current and prior quarter,

$$r^{loan}_{i,t} = \frac{IntInc_{i,t}}{Loans_{i,t} + Loans_{i,t-1}} \times 8 \tag{12}$$

We are able to do this separately for residential mortgages (RRE) and all other (AO) loans after 2007:Q4. However, prior to this quarter interest income is not broken out between these two categories so we define loan rates (and by extension risk premia) for the total loan portfolio.

Implied loan rates have both negative realizations and extreme outcomes in the right tail, particularly as balances approach zero. We set a minimum loan rate of 10ps for the left tail and we winsorize the top 1% in the right tail by date. Banks without a relevant loan balance are recorded as missing. We use these loan rates to infer the riskiness of each loan portfolio. The implied loan rates reflect the interest income earned relative to the book value of the loan portfolio, hence they reflect the yield on loans at the time of origination. As a result, loan rates for fixed-rate loans do not correspond to prevailing market yields, but rather to yields at the time the loans were originated. Loan rates and average maturity of loan portfolios are summarized in IA Table IA8,.

Rating bounds: To infer the riskiness of each loan portfolio, we compare bank loan rates to bank-specific upper and lower rating bounds that approximate the yield on a loan portfolio with a similar maturity structure. Based on banks loan rates relative to these bounds, we assign each bank a risk premium. We generate bank specific bounds because credit spreads are typically increasing with maturity, hence a long maturity portfolio will tend to have higher rates than a short maturity portfolio with similar risk.

We construct lower bounds using the High Quality Market (HQM) corporate bond yield curve calculated by the U.S. Department of Treasury that estimates the corporate curve for a portfolio of AAA to A bonds. We infer yields at a range of maturity horizons, m, and average daily yields over each quarter, t, to obtain yields, $cc_{t,m}$, that reflect a AA credit portfolio. Loan portfolios are reported for five maturity categories: less than six months, six to twelve months, one year to three years, three years to five years, five years to fifteen years, and over fifteen years. Using the portfolio share for each of these maturity categories we calculate the weighted average yield implied by the HQM yields for each bank, i, at each quarter, t,

$$\begin{aligned}AA_{i,t} = & cc_{t,6m}^{2QMA} Share_{i,t,6m} + cc_{t,9m}^{2YMA} Share_{i,t,6-12m} + cc_{t,2y}^{4YMA} Share_{i,t,1-3y} \\ & + cc_{t,4y}^{5YMA} Share_{i,t,3-5y} + cc_{t,10y}^{7.5YMA} Share_{i,t,5-15y} + cc_{t,20y}^{7.5YMA} Share_{i,t,>15y}.\end{aligned}$$

Yields on loan portfolio reflect the historical yields at origination rather than current yields for most maturities. Therefore, each loan portfolio is composed of yields originated over time rather than the spot yields reported by the HQM. To account for this when we construct the AA bound, we make two adjustments to corporate yields. First, we winsorize the implied spread relative to the corresponding GSW yield (the top 10%), as these extreme spreads reduce issuance so they are not particularly informative of actual loan yields. This step primarily reduces extreme spreads observed during the GFC. Second, we use moving averages of $cc_{t,m}$ to reflect yields over recent history. At the six month horizon we use a relatively short, two-quarter moving average, as this category includes floating rate instruments. For the nine-month, two-year, and four-year maturities we use a two-year, four-year and five-year moving average respectively. For the ten-year and twenty-year horizons we use a seven-and-a-half year moving average.

The lower bound corresponds to the corporate bond index for AA rated bonds. For the upper bound, we use the average between the BB and B (BB-B) OAS spreads. To obtain the upper bound for each bank we scale up the lower bound to reflect the proportional difference

Table IA8: Loan rates, rating bounds, and risk premia. This table summarizes key statistics involved in assigning loan portfolios risk premia. For loan portfolios, the table provides implied loan rates, approximate years to maturity, and the lower (AA rated) and upper (BB/B rated) bounds, and the risk premium of the portfolio. Prior to 2008, these values are for the total loan portfolio. From 2008 onward, statistics are reported separately for RRE (1-4 family first lien mortgages) and AO (All Other) loans. For each of these time periods, we report the corporate yields and option adjusted spreads from the ICE US Corporate Bond Indices. Distributions of implied loan rates are bounded at 10bps on the left while the top 1% of realization by date are winsorized. Bounds are implied by the maturity of the loan portfolio, the AA and BB/B spreads, and the corporate credit curve.

	Mean	Median	SD	Min	Max	N
<2008:Q1						
Total loans						
Implied rate	8.15	8.16	1.46	0.10	14.32	311,843
Years-to-maturity	3.36	2.63	2.43	0.25	22.50	311,898
AA bound	5.23	5.31	1.17	1.32	8.05	311,898
BB-B bound	8.66	8.88	1.20	3.42	12.55	311,898
$rp_{i,t}$	2.67	2.44	1.29	0.38	8.41	311,843
Corporate yields						
AA	5.42	5.51	1.20	3.04	7.53	311,854
BB-B	8.96	8.55	1.71	6.38	12.35	311,854
AA OAS	0.77	0.69	0.29	0.38	1.68	311,854
BB-B OAS	4.22	3.66	1.69	2.30	8.41	311,854
≥2008:Q1						
RRE loans						
Implied rate	5.57	5.40	1.53	0.10	21.37	374,825
Years-to-maturity	7.32	5.81	4.93	0.25	22.50	374,954
AA bound	3.18	3.15	1.08	0.16	6.24	374,954
BB-B bound	6.51	6.58	1.65	0.55	12.35	374,954
$rp_{i,t}$	2.85	2.43	2.02	0.48	14.83	374,825
AO loans						
Implied rate	5.51	5.40	1.28	0.10	11.79	378,967
Years-to-maturity	4.11	3.45	2.47	0.25	22.50	379,015
AA bound	2.68	2.49	1.02	0.16	6.24	379,015
BB-B bound	5.51	5.35	1.47	0.55	12.35	379,015
$rp_{i,t}$	3.39	3.03	1.92	0.48	14.83	378,967
Corporate yields						
AA yield	3.30	2.76	1.27	1.42	7.05	379,068
BB-B yield	6.94	6.45	2.42	3.81	16.39	379,068
AA OAS	1.14	0.88	0.82	0.48	4.19	379,068
BB-B OAS	4.84	4.22	2.36	2.41	14.83	379,068

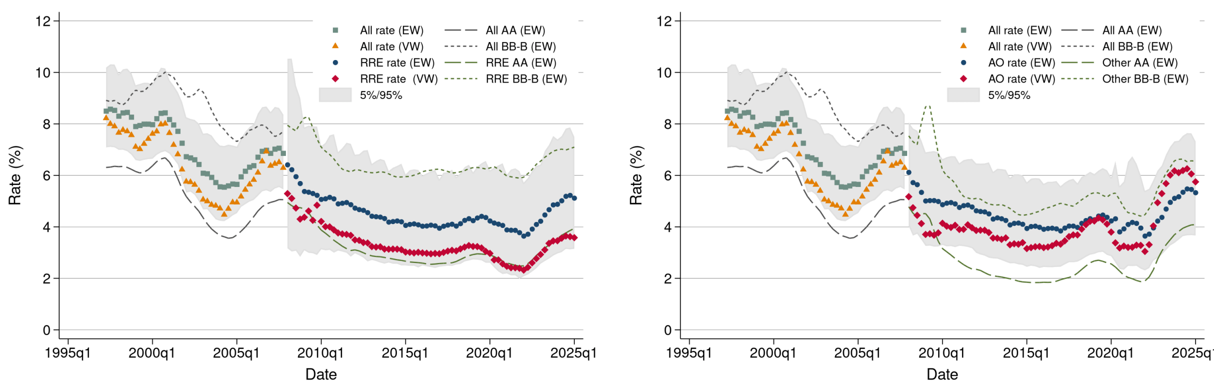
between AA and BB-B OAS spreads for each quarter. Each bank has a lower bound that corresponds with a portfolio of AA rated loans and an upper bound that corresponds with

BB-B rated loans. These bounds are constructed separately for RRE loans and AO loans from 2008 onward and for the total loan portfolio prior to 2008.

The bounds are reported in Table IA8 and illustrated over time in Figure IA9. In the table, we can see that for total loans and AO loans both bounds are materially lower than their respective corporate yields whereas RRE bounds are similar to corporate yields. These differences are explained by the shorter average maturity of total loans and AO loans than the corporate bond indices, whereas RRE loans have a similar maturity structure as a corporate bond index (6-7 years). The figure depicts how the average bounds vary over time relative to the distribution of loan rates.

Figure IA9. Loan rates and rating bounds. This figure plots the distribution of loan rates and the average upper and lower risk bounds. We consider the total loan rate for the period prior to 2008:Q1 and RRE (Fig. IA9a) AO (Fig. IA9b) loans separately for the period after 2008:Q1. Reported loan rates are lowered by 100bps to reflect the premium of loan pricing to comparable corporate bonds. The figures include equalweighted means and valueweighted means as well as the 5-95th percentile range. For the lower (AA) and upper (BB-B) bounds, we include equalweighted means to illustrate how bounds vary over time with respect to rates.

(a) Total and RRE loans **(b)** Total and AO loans



Risk premia: Using the bank specific rating bounds, we assign risk premia to each bank ranging from a AA corporate rating to the average of the BB and single-B corporate rating (BB-B). To do so, we compare bank loan rates less 100bps, $r_{i,t}$, to the upper and lower bounds. We subtract 100bps based on the literature that finds bank loans earn rates on loans that are 125bps to 140bps higher than comparable bonds (Schwert, 2020). This range is on the lower end of estimates of the marginal cost of lending cost generated by Corbae and D'Erasmo (2021) of 1.13 percent of assets (Corbae and D'Erasmo, 2021). Loan portfolios are assigned a rating, $\omega_{i,t}$, that ranges from 0 for loan portfolios with rates less than or equal to the AA lower bound to 1 for loan portfolios that exceed the upper bound.

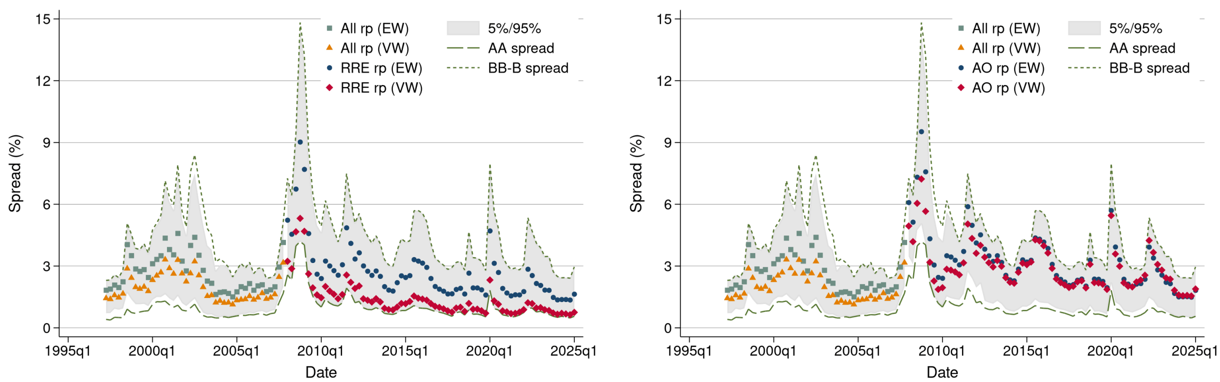
$$\omega_{i,t} = \begin{cases} 0, & \text{if } r_{i,t} \leq \text{AA}_{i,t}, \\ \frac{r_{i,t} - \text{AA}_{i,t}}{\text{BB-B}_{i,t} - \text{AA}_{i,t}}, & \text{if } \text{AA}_{i,t} < r_{i,t} < \text{BB-B}_{i,t}, \\ 1, & \text{if } r_{i,t} \geq \text{BB-B}_{i,t}, \end{cases} \tag{13}$$

To minimize non-fundamental volatility in credit risk assignments, we take up to the 4-quarter moving average, $\overline{\omega_{i,t}}$, and then calculate the credit spread for each loan portfolio using the OAS spreads on the corresponding ICE US bond indices.

$$rp_{i,t} = (1 - \overline{\omega_{i,t}})OAS_t^{AA} + \overline{\omega_{i,t}}OAS_t^{BB-B}. \tag{14}$$

Figure IA10. Loan risk premia. This figure plots the distribution of assigned risk premia, $r_{i,t}$ and the spreads that bound assigned risk premia. We consider the total loan rate for the period prior to 2008:Q1 and RRE (Fig. IA9a) AO (Fig. IA9b) loans separately for the period after 2008:Q1. The figures include equal-weighted means and value-weighted means as well as the 5-95th percentile range.

(a) Total and RRE loans   **(b)** Total and AO loans



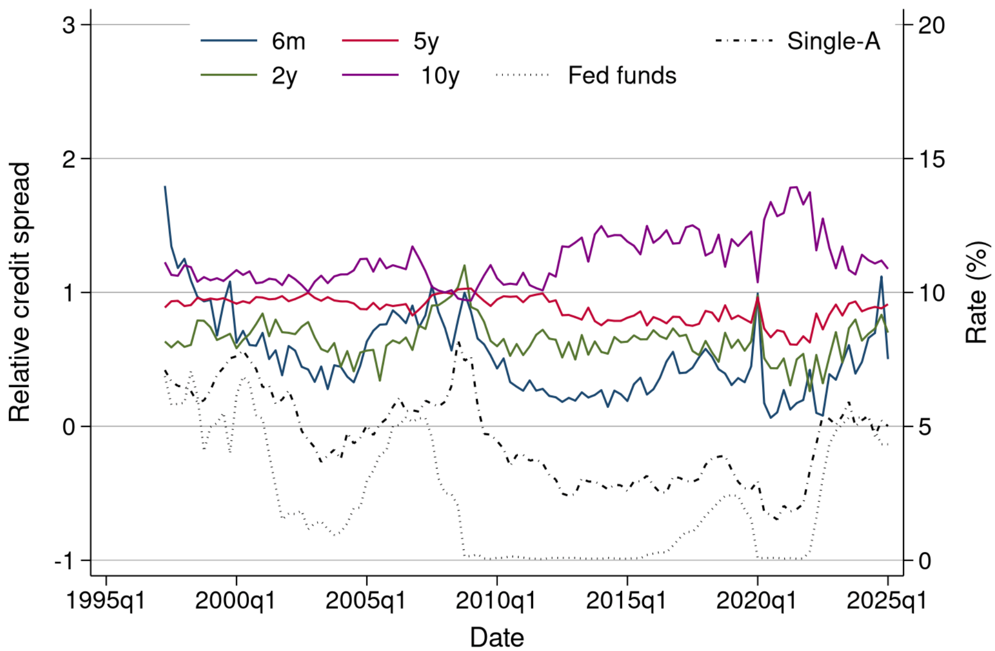
The final step is to adjust the assigned risk premia for specific time-to-maturity buckets so that the assigned premium is consistent with the maturity of the loan portfolio. We use the end of quarter spot rates from the HQM corporate credit curve to infer the term structure of corporate spreads at each of our time-to-maturity horizons, m. We apply the term structure of credit spreads to the bank specific risk premium, $rp_{i,t}$ to recover a risk premium for each time-to-maturity bucket, $rp_{i,t,m}$. We use the corporate bond curve and assign each maturity a factor relative to the six-year maturity ($m = 24$), as six years appears to most closely reflect the maturity of the single-A, BBB, and BB/B corporate bond indices.[6] We multiply this factor by the bank-specific credit spread to get the risk premium for each time-to-maturity up to ten years; beyond ten years, we assume the risk premium is flat.

$$rp_{i,t,m} = rp_{i,t}\frac{cc_{t,m}}{cc_{t,24}}. \tag{15}$$

The process assumes that the relative shift in spreads is similar across the a range of ratings. Calculating maturity specific spreads has a material impact on the risk premium applied to banks as there are meaningful differences in credit spreads across the maturity distribution and these differences vary over time, Figure IA11.

[6]The OAS spreads from the bond indices most closely track a maturity between 5 and 7 years.

Figure IA11. Relative corporate credit spreads over time. This figure plots the evolution of relative corporate credit spreads, $\frac{cc_{t,m}}{cc_{t,24}}$. Corporate spreads are based on the Department of Treasury HQM corporate spreads. For comparison purposes, we include relative spreads for the 6-month, 2-year, 5-year, and 10-year.

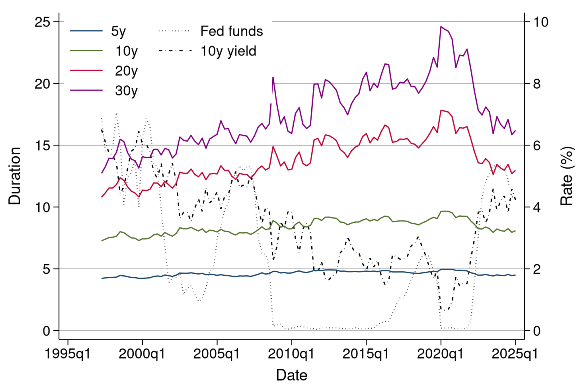


B.7 Implied durations

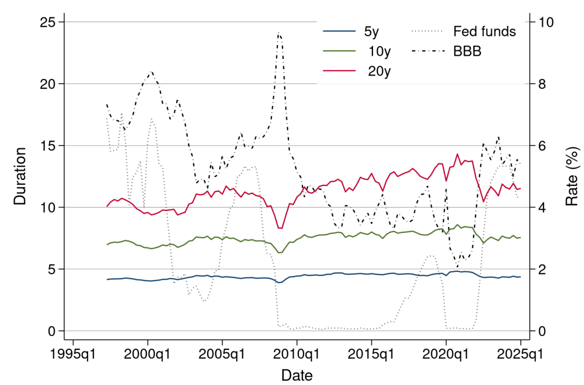
Our methodology for portfolios with fixed-rate instruments implies durations for the full range of time-to-maturity buckets, m, ranging from 1 quarter to 120 quarters (30 years). The implied duration by maturity varies with the choice of discount factor and prepayment rates. Figure IA12 illustrates how risk premia and prepayment impact duration for asset portfolios (e.g., loans). The risk-free durations, Figure IA12a, increase with the time-to-maturity with the longest maturity buckets most sensitive to the discount rate, rising as the discount rate falls. Including the BBB spread as the risk premium, Figure IA12b, lowers durations, especially for longer maturity buckets and during periods of elevated credit risk. Introducing prepayment and heterogenous risk for RRE loans and All Other loans, Figures IA12c and IA12d, significantly reduces implied duration, especially during high prepayment periods.

Figure IA12. Time-series of implied asset duration by time-to-maturity and instrument type. This figure plots the implied duration of assets for a range of time-to-maturity buckets for several different discount rates and prepayment assumptions. The plots contain the fed funds rate and either the ten-year yield or the yield on an index of single-A credits. Figure IA12a depicts implied durations using risk-free rates. Figure IA12b includes a single risk premium equivalent to the BBB spread. Figures IA12c and IA12d show the range of durations using our estimates of heterogeneous risk premia (Figure IA10) and prepayment for RRE and all other (AO) loans, respectively. The low risk durations (AA) are depicted in solid lines and the high risk durations (BB-B) are depicted in the dotted lines.

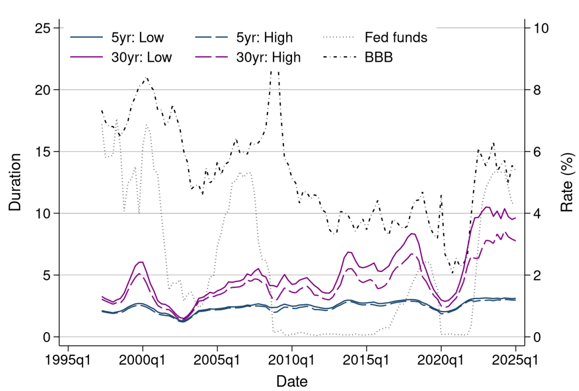
(a) Risk-free: rf_t



(b) Risk premium: $rf_t + rp_t$ (BBB)



(c) RRE loans: $rf_t + rp_{i,t}$ & prepay



(d) AO loans: $rf_t + rp_{i,t}$ & prepay

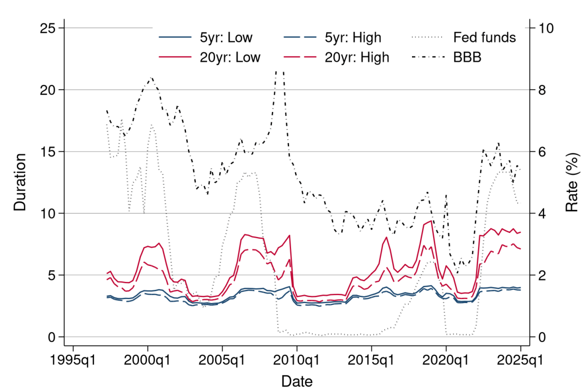
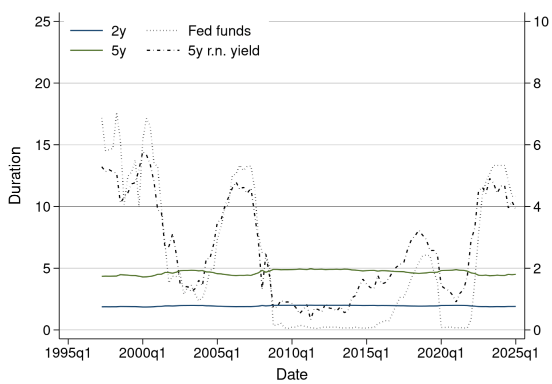


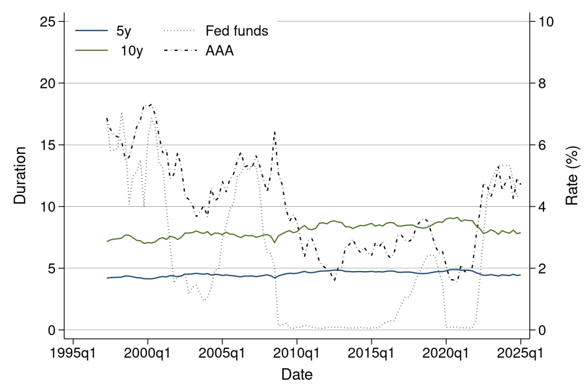
Figure IA13 illustrates how implied duration varies across liability time-to-maturity buckets. Liabilities use relatively risk-free rates and do not allow for prepayment. Liabilities also cover a a shorter range of maturities than assets. For time deposits and other borrowing we use risk neutral yields; the range of durations is depicted in Figure IA13a. For subordinated debt we use constant-maturity yields plus the AAA credit spread implied by the ICE corporate bond index, Figure IA13b.

Figure IA13. Time-series of implied liability duration by time-to-maturity and instrument type. This figure plots the implied duration for a range of time-to-maturity buckets for the discount rates used for time deposits, other borrowing and subordinate debt. The plots contain the fed funds rate and either the five-year risk neutral yield or the yield on an index of AAA credits. Figure IA13a depicts implied durations using ACM risk-neutral rates. Figure IA13b reports durations using GSW yields plus the AAA spread. The former durations are applied to time deposits and other borrowing, the latter to subordinated debt.

(a) Risk-neutral: rn_t



(b) Risk premium (AAA): $rf_t + rp_t$ (AAA)



B.8 Validating loan values

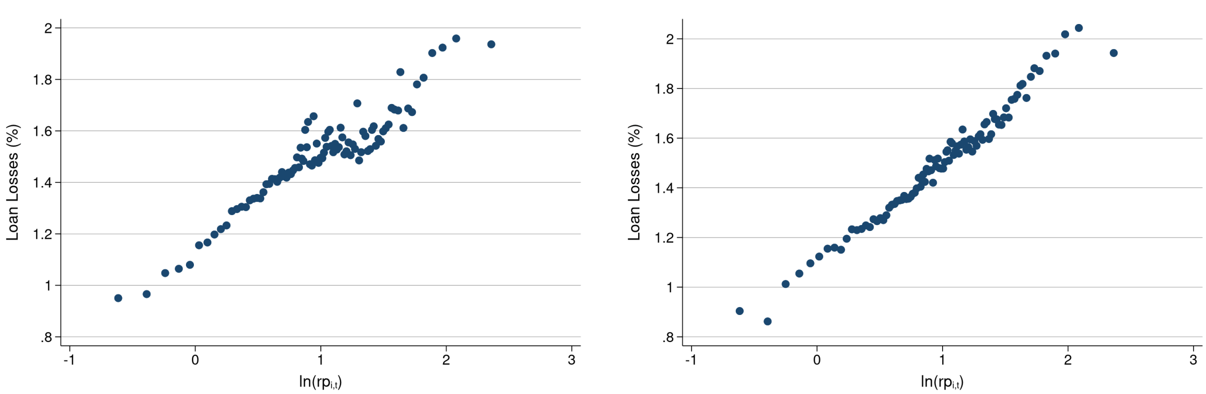
We validate our loan values by first assessing whether the assigned risk premia are associated with greater loan losses and second by comparing our estimated loan values to loan values reported by a subset of banks.

B.8.1 Risk premia and losses

In this section we demonstrate that the risk premium we assign to loan portfolios are associated with future loan loss reserves. Figure IA14 depicts the correlation between loan losses and lagged risk premia assigned to the loan portfolio using bin scatters. Table IA9 demonstrates that the risk premium predicts loan losses at the three-year horizon. Higher risk is associated with greater loan losses. The association is robust to date fixed effects (Column 2), lagged loan losses (Column 3) and Entity fixed effects (Column 4). Hence the assigned risk premia appear to help explain the credit risk of the bank in both the cross-section and over time. The results are statistically significant at the 1% level. While the risk premium is predictive, the vast majority of credit risk is difficult to predict (the adjusted R-squared is only .03).

Figure IA14. Correlation of risk premium and loan losses. This figure plots the correlation of lagged loan portfolio risk premium ($\ln(rp_{i,t-12})$) and the loan loss percentage (reserves relative to total loans at time t) in the full sample from 1997 to 2025. Figure IA14a contains a bin scatter of 3-year lagged risk premia and loan losses. Figure IA14b contains the same variables, but conditions on date fixed effects. Bins are data-driven as per Cattaneo et al. (2024).

(a) No Fixed Effects **(b)** Date Fixed Effects



B.8.2 Comparing to reported fair values

Public banks report estimated fair values of their loan portfolios in SEC filings. These banks are typically BHCs, which can contain multiple bank subsidiaries. For comparison purposes we aggregate our loan value estimates across subsidiaries and scale by the book value of loans. This sample results in 14,657 observations from 2010:Q1 onward. The bin scatter in Figure IA15a illustrates that there is a positive correlation that is roughly 1:1 with our present value estimates and those reported by banks in this sample when these

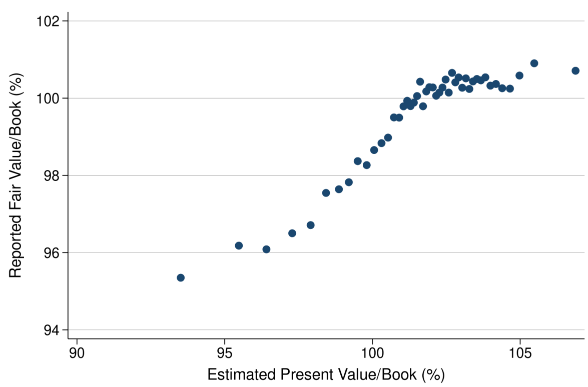
Table IA9: Predicting loan losses with assigned risk premia. This table reports coefficients from regressions of loan loss reserves on lagged risk premia. The dependent variable is a bank's loan loss reserves divided by their total loans gross of reserves. The independent variables are lagged three-years and include the log of the assigned risk premium, loan loss percent, and fixed effects. Standard errors are clustered by bank and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
$\ln(rp_{i,t-12})$	0.33***	0.41***	0.20***	0.07***
	(0.02)	(0.02)	(0.02)	(0.03)
Loan $\text{Losses}_{i,t-12}$ (%)			0.56***	0.19***
			(0.04)	(0.05)
Constant	1.17***	1.09***	0.47***	1.14***
	(0.03)	(0.02)	(0.05)	(0.08)
Observations	554589	554589	554588	554412
Adj. R^2	0.03	0.06	0.32	0.52
Fixed Effects				
Y mean	No	Yes	Yes	Date & Bank
ymean	1.49	1.49	1.49	1.49

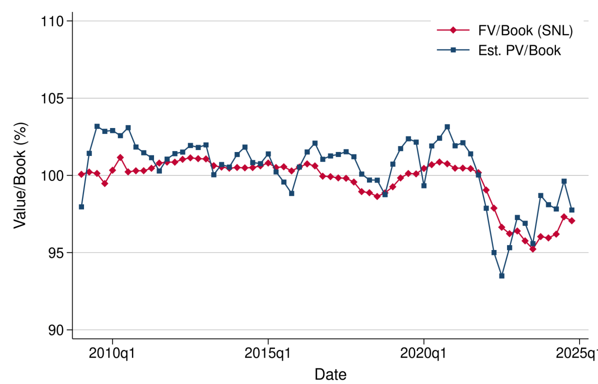
values range from 95% of book value to just above 100%. At the more extreme estimated values the relationship is an attenuated. Figure IA15b depicts the average over time and shows that our estimated present value is more volatile than the fair values reported by banks. The additional volatility corresponds to changes in the level of the risk premium: low risk premium episodes are associated with higher loan values and high risk premia lower values. This suggest methodological differences in the treatment of risk premia between our approach and bank approaches; however the averages are quite similar. From the perspective of conservatism, a greater sensitivity to the risk premium will generally results in more conservative estimates of solvency when spreads widen.

Figure IA15. Correlation of loan present values to reported fair values. This figure plots the correlation of estimated loan present values with bank estimates of loan fair values in the cross section, Fig. IA15a, and in the time series, Fig. IA15b. Bank reported fair values are from SEC filings of public BHCs as reported by S&P SNL. Estimated present values are our estimates. Bins are data-driven as per Cattaneo et al. (2024).

(a) Bin scatter



(b) Time Series Average



C Demand deposits

C.1 Deposit rates and composition

We pool interest-bearing (IB) and noninterest-bearing (NIB) demand deposits for the purpose of capturing deposit prices and estimating deposit betas. Hence, estimates of deposit betas implicitly allow for mix shifts between types of deposit accounts. We do this separately for domestic and foreign demand deposits as foreign deposits are not easily substituted for domestic and pricing behavior appears materially different. We treat time deposits as distinct given their high sensitivity to interest rates and unique maturity structure.

As with loans, we calculate implicit annual deposit rates for domestic and foreign demand deposits as the quarterly interest expense on non-time deposits for each bank i and each quarter t divided by the average deposit balance between the current and prior quarter,

$$r^D_{i,t} = \frac{IntExp_{i,t}}{Deposits_{i,t} + Deposits_{i,t-1}} \times 8 \tag{16}$$

We censor deposit rates at zero on the left hand side and winsorize the top 50bps and top 250bps on the right hand side for domestic and foreign deposits, respectively. Doing so eliminates rare but extreme outliers such as negative interest rates or extremely high implied deposit rates that confound inference of typical deposit behavior. The time-series of implied rates is depicted in Figure IA16.

Figure IA16. Implied demand deposit rates. This figure plots implied demand deposit rates over time for domestic and foreign deposits. In addition, the plot includes the average quarterly fed funds rates and shades periods where the fed funds rate is rising. Both plots consider the industry (solid lines) and the average (dotted lines).

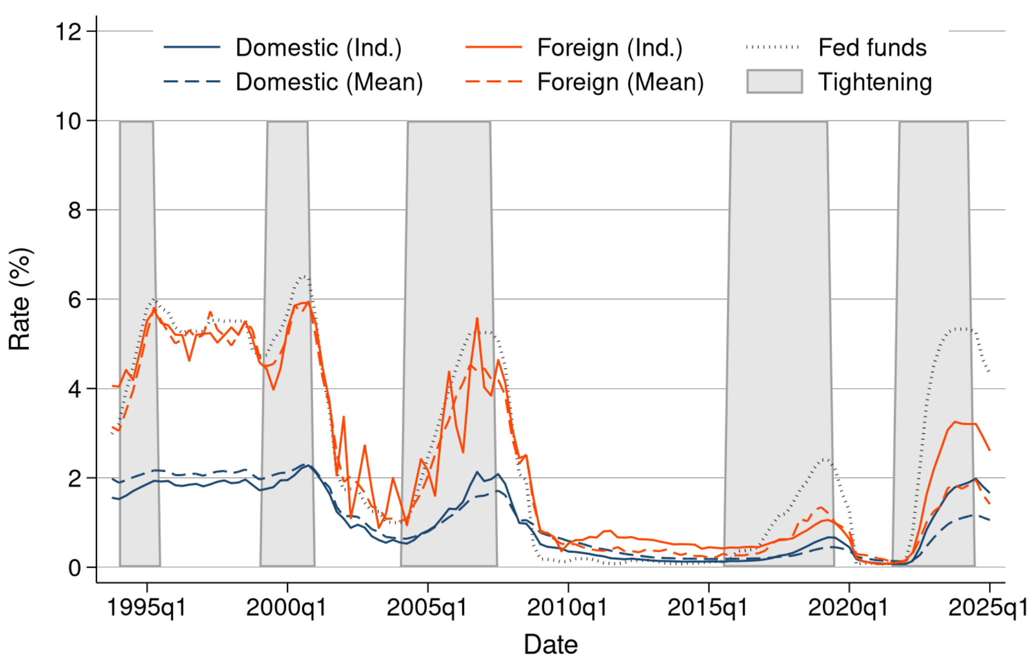
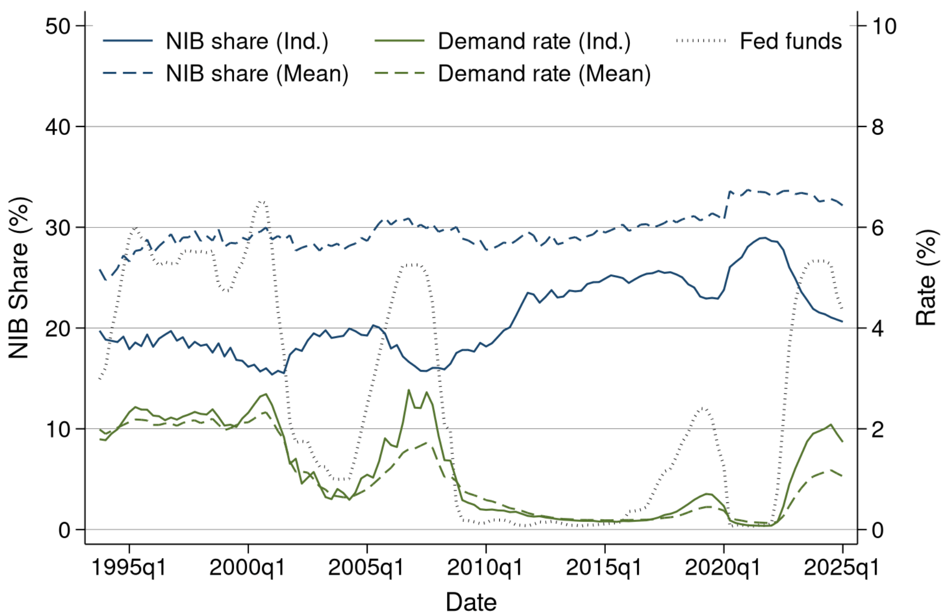


Figure IA17 illustrates the industry and average NIB deposit share relative to total demand deposits as well as the implied overall rate on demand deposits. Particularly for larger banks, NIB deposit mix is inversely related to the fed funds rate, increasing the responsiveness of the deposit rate to interest rates.

Figure IA17. Demand deposit composition. This figures plot deposit composition over time, specifically the share of noninterest bearing deposits relative to demand deposits and the implied overall demand deposit rate. The plot includes the weghted mean (i.e., the industry) and the simple average.

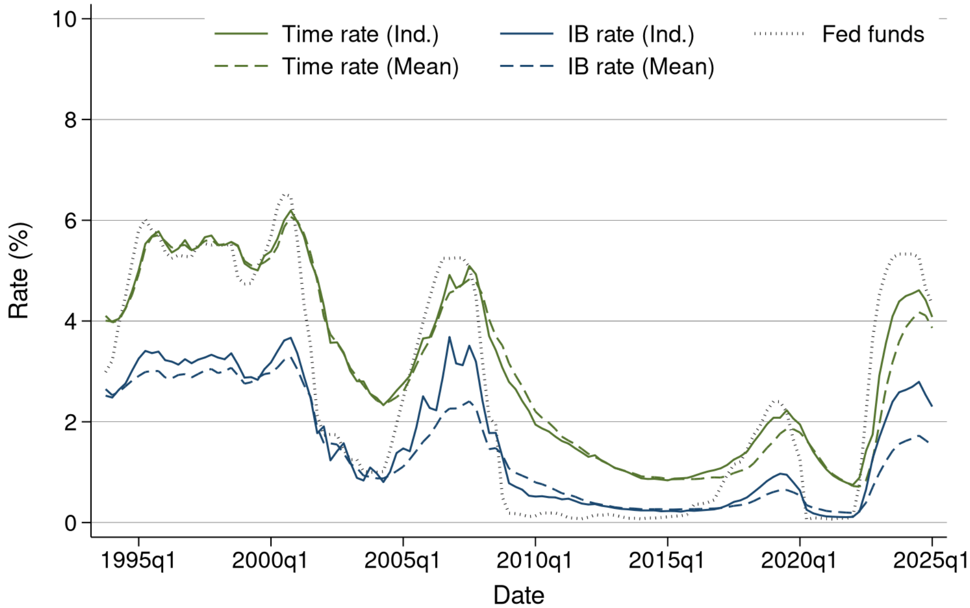


Time deposit behavior is distinct from demand deposits. While time deposit share is also cyclical, Figure IA18 shows the implied time deposit rates track much more closely with the fed funds rate than IB demand deposits. Moreover, the maturity structure of time deposits means they respond slowly to rate declines. The ratio of average and industry time deposit rates to the fed funds rate is 1 on average and greater than 1 in a falling rate environment. Overall, time deposits do not appear to possess a meaningful cost advantage to other incremental funding sources, they have different pricing dynamics than IB deposits, and they carry valuation risk in a falling rate environment.

C.2 Deposit valuation

Our conceptual approach to valuing deposits is illustrated by the key parameters of a perpetuity in Equation 4. In practice, we use a more nuanced formula that incorporates the slope of the yield curve over the next five years before applying the perpetuity value. To do so, we discount payments and drawdowns for the first five years before applying the perpetuity

Figure IA18. Time deposit rates. This figure plots the time deposit rates and the rate on IB deposits. The plot includes the weighted mean (i.e., the industry) and the simple average.



to generate the present value of demand deposits per dollar of book value,

$$DD_{i,t} = \sum_{k=1}^{5} (1-\delta)^{k-1} \frac{\beta_{i,t}^{k} f_t^{k} + \delta}{(1+y_t^k)^k} + \left(\frac{1-\delta}{1+y_t^5}\right)^5 \frac{\beta_{i,t} f_t^{5-10} + \delta}{f_t^{5-10} + \delta}, \tag{17}$$

where t is the quarter and k is the time horizon. The forward rate, f is inferred from the discount rate, y, at specific time horizons, including the 5 to 10 year horizon, f^{5-10}. Long-term deposit betas, $\beta_{i,t}$, are predicted based on the empirical model described below. Near-term betas at each horizon, $\beta_{i,t}^k$, are equal to the long-term estimates as long as the corresponding forward rate is greater than 25bps. Below 25bps we set beta to one to reflect that deposit rates tend to exceed fed funds rate near the ZLB (See Table IA11). The PV-per-dollar, DD, is multiplied by the book value of demand deposits to obtain the present value in dollars. Relative to Equation 4, the key intuition remains but we obtain modestly different estimates ($< 5\%$ at typical parameter values). In an elevated, flat rate environment, the results are identical.

Deposit value is increasing in both betas and drawdowns — higher values of either suggest a greater share of deposits are paying prevailing interest rates. Moreover, these two parameters are jointly determined under typical market conditions as banks select a deposit rate based on their desired level of deposits. Therefore, we choose to fix a common drawdown rate and estimate differences across banks as originating from differences in betas conditional on drawdowns. Consistent with microdata of stable deposit franchises we choose to use a 5% drawdown rate. The choice of rate is based on microdata on deposit retention (Sherman, 2013) where the median bank has an average checking and savings account life of 19.5 years.

C.3 Deposit sensitivities

Our empirical approach is designed to recover long-term deposit betas. There are several ways to model the sensitivity of deposit rates to interest rates, including ratios, relative changes, and spreads. We focus on the ratio as it provides stable estimates and is easily mapped into valuation, however we find broadly similar results across alternative approaches. For the final quarter of each interest rate tightening cycle, T, the measure of interest is:

$$B^R_{i,T} = \frac{r^d_{i,T}}{ff_T}$$

where $r^d_{i,T}$ is the implied demand deposit rate, ff_T is the average daily fed funds rate in quarter T.

We choose the final quarter of tightening cycles because they reflects the most relevant observation for long-term valuation: ultimate sensitivities at elevated rates (the ACM risk-neutral yields never fall below 1.9%). Over the past five cycles, Figure IA19, B^R ratios are elevated early in a cycle but tend to decline before rising slightly. Each cycle trends toward similar levels with the exception of the 2015-2019 period.

Figure IA19. Tightening cycles and deposit sensitivities. These figures plot deposit betas over the course of five recent tightening cycles. We present average betas equal-weighted (EW) and asset-weighted (AW) for both relative betas, B^R, and cumulative betas, B^C.

(a) EW B^R : Ratio

(b) AW B^R : Ratio

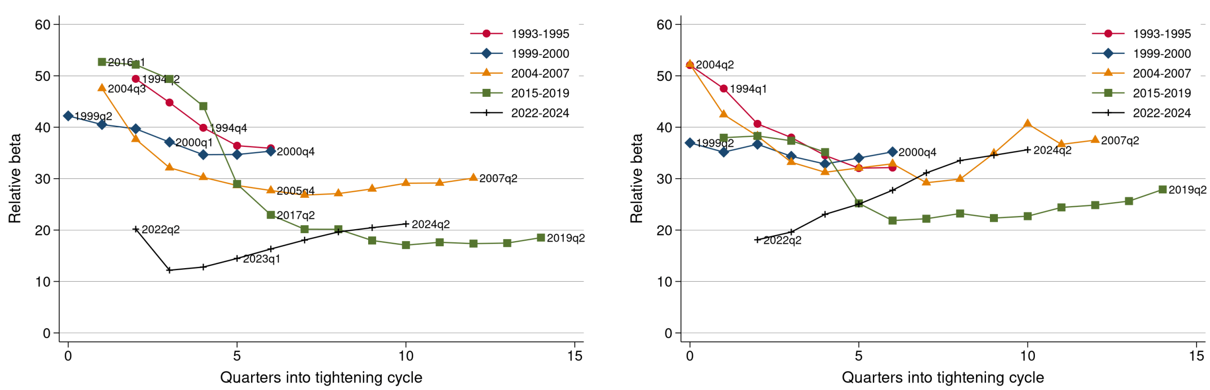


Table IA10 summarizes the tightening cycles and deposit behavior. These cycles vary in their length, the ultimate level of interest rates and the change in the fed funds rate. In addition, there is significant bank-level heterogeneity in the sensitivity of deposit rates and the growth in demand deposits. The interquartile range of deposit rates to the fed funds rate is roughly two-thirds that of the average ratio, 29.8, and the interquartile range of deposit growth is three times the average growth of 2.9%. Our estimation of deposit sensitivities will condition on cycle and bank differences so we can create estimates of deposit betas that reflect the heterogeneity in the data.

A limitation of our empirical approach is that it does not consider deposit sensitivities in low rate environments. Table IA11 illustrates that the deposit sensitivity has a median of

Table IA10: Summary statistics for domestic demand deposits in tightening cycles. This table reports the average demand deposit behavior over five prior tightening cycles along with the interquartile ranges. All measures are in percentages. Columns include the ultimate fed funds rate (ff), the change in the fed funds rate over the cycle (Δff), the ultimate implied demand deposit rate (r^D), our measures of relative deposit pricing, and the annual log growth rate in demand deposits over the cycle. Fed funds rate and deposit rates are the average over the final quarter of the cycle.

	Fed Funds		Demand deposits (Mean & IQ Range)			
	ff	Δff	r^D	Δr^D	B^R	Growth
1993q4-1995q2	6.02	3.03	2.17	0.17	35.92	-1.01
			0.65	0.45	10.68	10.93
1999q2-2000q4	6.47	1.73	2.32	0.26	35.34	7.69
			0.97	0.52	14.54	11.63
2004q2-2007q2	5.25	4.24	1.66	0.94	30.08	4.46
			1.15	0.95	20.19	9.99
2015q4-2019q2	2.40	2.24	0.45	0.26	18.53	5.41
			0.40	0.33	16.54	6.82
2021q4-2024q2	5.33	5.25	1.14	0.99	21.18	-2.49
			1.09	1.05	20.19	7.73
Average	5.31	3.17	1.69	0.48	29.77	2.90
			1.43	0.69	19.02	11.04

200% when the fed funds rate is less than 25bps, but otherwise the median sensitivity ranges from 40 to 46. The relevant forward rate beyond five years never falls below 1.9%, hence our long-term beta estimates are reasonable given observed future rates. When we extrapolate near term betas in Equation 17 we make adjustments for maturities where the future rate is less than 25bps.

C.3.1 Estimated betas

The existing literature on deposit pricing largely considers pricing as independent from growth. Ideally, we would obtain the supply curve bank's face when they make deposit pricing decisions and then select a beta on the curve consistent with a 5% drawdown rate. A structural approach to deposit supply is challenging given that demand deposits are a heterogeneous product that combines local markets, with retail and small business deposi-

Table IA11: The ratio of deposit rates to fed funds, B^R. This table reports the average ratio of deposit rates to the fed funds rate by levels of the fed funds rate. All measures are in percentages. Fed funds rate and deposit rates are the average over the quarter.

Fed funds level:	Mean	Median	p5	p95	N
≤ 25 bps	265.3	201.4	46.1	703.3	211,455
$25 - 50$ bps	49.6	40.4	11.7	121.0	22,103
$50 - 100$ bps	72.9	39.9	6.8	254.7	29,019
$100 - 150$ bps	51.3	46.6	7.9	114.6	70,403
> 150 bps	39.0	37.2	8.1	76.5	472,160
Total	101.0	45.9	9.9	410.3	805,140

tors, and national markets, with brokered and corporate depositors. We take a reduced form approach using a hedonic regression that reflects deposit heterogeneity, is robust to various specifications and is consistent with expected deposit supply relations. A more structural approach to deposit supply and demand — that can distinctly identify supply and demand elasticities by depositor type — could further refine these estimates (e.g., Egan et al., 2017).

To generate a panel of long-term betas, we develop an empirical model using a hedonic regression that explains the ultimate deposit sensitivities using bank and cycle characteristics. We estimate a linear regression for bank i and cycle T,

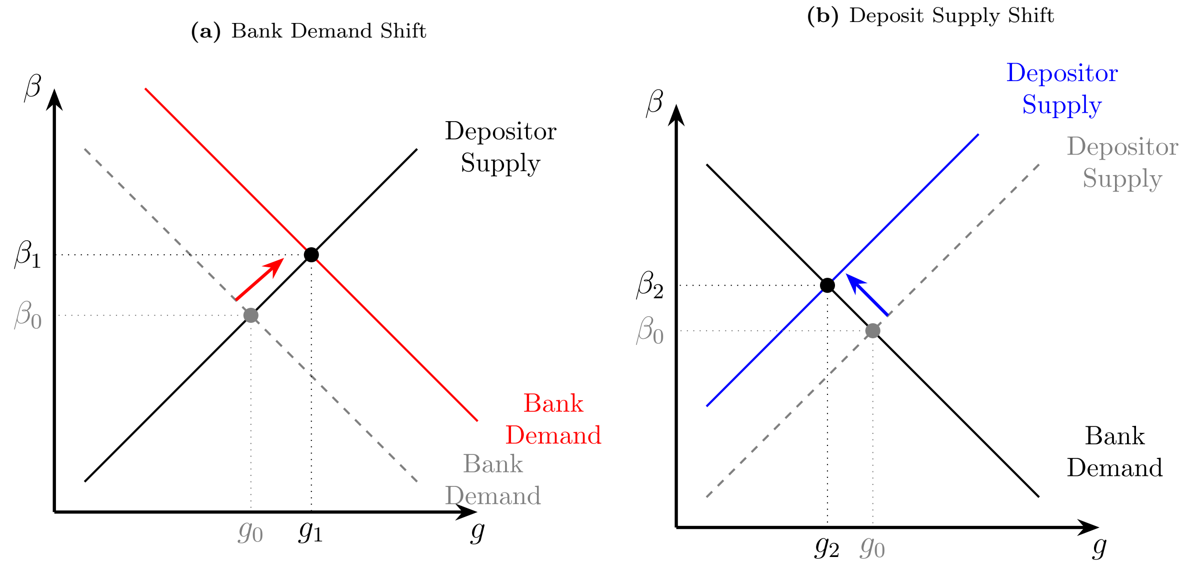
$$B_{i,T} = \alpha + \mathbf{\Gamma X}_{i,T} + \mathbf{\Theta Z}_T + \kappa g_{i,T} + \varepsilon_{i,T}, \tag{18}$$

where the ultimate sensitivity for each bank, $B_{i,T}$, is regressed on bank characteristics at the start of the cycle, $\mathbf{X}_{i,T}$, cycle characteristics, $\mathbf{Z}_T$, such as the length of the cycle and the ultimate level of interest rates, and annual deposit growth over the cycle, $g_{i,t}$. We consider specifications that include time and bank fixed effects to confirm that our coefficients are robust to specifications that absorb cycle- and bank-specific differences.

Estimation of the relation between price and quantities (i.e., deposit sensitivities and growth) is subject to potential simultaneity bias — in the cross-section higher betas may be a response to greater demand or higher betas may reflect lower supply (see Figure IA20). If cross-sectional differences in growth reflect shifts in the deposit supply, Figure IA20b, rather than bank demand, Figure IA20a, then our coefficients may be biased and, in particular, the coefficient on deposit growth would be attenuated. We will show that the coefficients are robust across various specifications, suggesting a lack of bias, that the relation is consistent with a supply curve, and that our estimates are conservative in the presence of an attenuated growth coefficient.

We considered a broad range of bank characteristics, but our estimates ultimately rely on those summarized in Table IA12. We find that focusing on bank characteristics that highlight the nature of the deposit base, such as the size of deposit accounts and features of the bank branch network, are important for explaining cross-sectional betas. This is consistent with these variables corresponding to mix of customers a bank services (retail,

Figure IA20. Deposits: Demand and supply. This figure illustrates the impact of supply and demand shifts on bank deposit betas (β) and deposit growth (g). Figure IA20a illustrates the impact of an outward shift in bank demand for deposits, whereby an increase in demand raises the interest rate relative to the fed funds rate and the growth of deposits. Figure IA20b illustrates a shift in deposit supply, whereby a decrease in supply increases the relative cost of deposits and reduces the growth rate.



high net worth retail, corporate, etc.). Additional factors such as bank size, deposit market concentration, and the percent of deposits that are insured are not statistically significant in these regressions.

With respect to time-series controls, we only include two factors as there are not many cycles with which to identify variation. We choose the length of the cycle, which tends to be correlated with higher betas, at least up to the maximum observed length of 14 quarters. We also include the final level of rates as betas tend to be higher at higher rate levels. For both variables we use the natural logs as the relations are nonlinear.

We find that growth is positively correlated with pricing, consistent with an upward sloping supply curve (depositors supply more deposits to banks with higher rates) (see Figure IA21).

The coefficient estimates from our regressions are summarized in Table IA13. Column (1) is the model used to predict long-term betas, as they exclude fixed effects. We find that initial deposit rates, the size of accounts, the share of MMDA accounts, and the concentration of deposits a few branches all correspond with higher sensitivity of deposits to rates. Each of these variables is associated with a particular type of client that is more price sensitive. Deposit growth is also positively correlated with pricing, consistent with higher rates attracting more deposits in the cross-section. With respect to time-series variables, sensitivities are higher for longer cycles, and for cycles with a higher ultimate rate.

When we include time fixed effects in columns (2) the cross-sectional coefficients remain similar in their magnitude and statistical significance and there is little change in adjusted R-squared. When we also include bank fixed effects in column (3), the coefficients for the ratio, B^R, are roughly the same, although we do obtain additional explanatory power suggesting that additional bank controls could further improve these estimates.

With respect to deposit growth and its potential to bias our estimates, the coefficients

Table IA12: Summary statistics for estimates of domestic deposit rate sensitivities. This table reports the summary statistics for the variables used to estimate demand deposit sensitivities over a hiking cycle. Deposit sensitivities are as of the end of a hiking cycle whereas bank controls are as of the beginning of the cycle. The lone exception is deposit growth which is measured over the cycle. Control variables with extreme skewness are winsorized. *Dep. rate/*f^{5-10} is the deposit rate divided by the risk-neutral forward rate at the 5-10 year horizon as of the start of the hiking period. *Deposits/Account* is the average size of deposit accounts at the bank in thousands of 2017 dollars and winsorized at the top 250bps. *Small acct. share* is the share of deposits that are held in accounts below the insurance threshold ($100k before 2008:Q4, $250k after). Interactions to account for the change in cut-off over time do not yield statistically significant results. *MMDA share* is the share of money market deposit accounts. *Deposits/Branch* is the total deposits in 2017 dollars per total number of branches winsorized at the top 250bps. *Deposit growth* is calculated as the per annum change in log deposits over the cycle for the industry.

	N	Mean	Med.	SD	Min	Max
Deposit sensitivities						
B^R: Ratio (%)	30,085	29.76	30.12	14.59	0.00	85.72
Bank controls						
Dep. rate/f^{5-10} (%)	30,085	30.38	29.71	22.38	0.00	98.38
Deposits/Account ($ '000s)	30,085	25.67	18.61	23.24	0.02	214.72
NIB share (%)	30,085	28.62	27.59	12.92	0.00	100.00
Small acct. share (%)	30,085	67.96	69.72	17.60	0.00	100.00
MMDA share (%)	30,085	25.13	22.11	17.70	0.00	100.00
Deposits/Branch ($ mm)	30,085	74.95	57.30	63.62	0.07	611.91
Deposit growth (%)	30,085	2.90	1.60	11.49	-30.77	70.31
Time-series controls						
ln(Cycle length)	30,085	2.14	2.30	0.36	1.79	2.64
ln(ff_T) (%)	30,085	1.62	1.67	0.33	0.87	1.87
Cycle length (Quarters)	30,085	9.07	10.00	3.23	6.00	14.00
ff_T (%)	30,085	5.29	5.33	1.34	2.40	6.47

appear generally stable when growth is excluded. In addition, deposit growth has a positive relation with deposit pricing, consistent with a conventional, upward sloping supply curve for deposits. This relation appears to be linear conditional on the other controls (see Figure IA21), which suggests that differences in bank demand are determining the sign of the coefficient. This does not rule out that the coefficient is attenuated due to unobserved demand shifts; however, attenuation will typically result in more conservative (i.e., higher) betas as more than 90% of banks exhibit growth rates in excess of our drawdown rate.

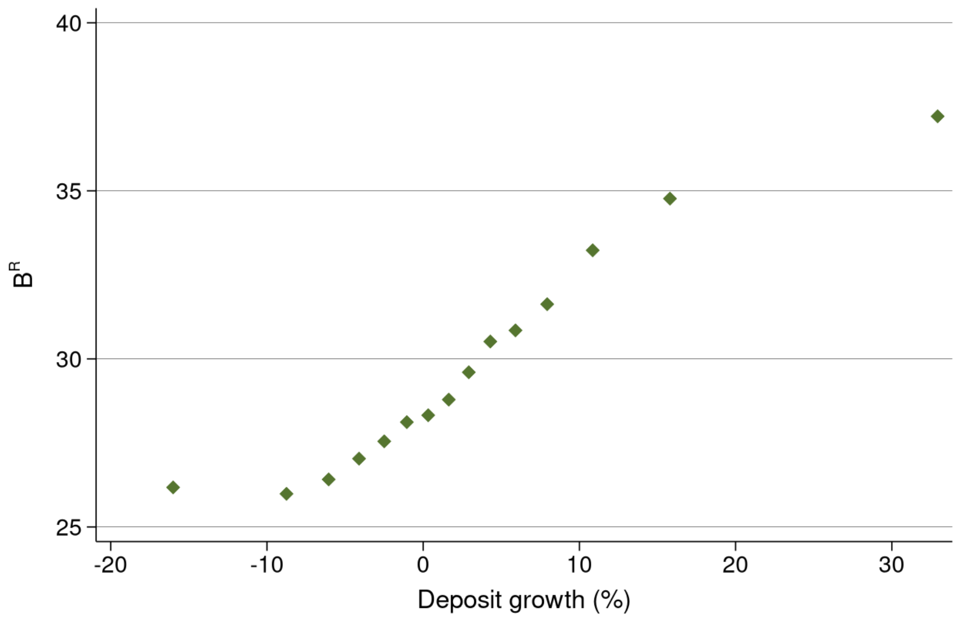
We use the coefficients from Column (1) to generate long-term estimates of deposit betas for each bank, i, and quarter, t. To do so, we seed the model with bank characteristics, $\mathbf{X}_{i,t}$,

Table IA13: Regression: Domestic deposit sensitivities in hiking cycles. This table reports the estimated coefficients from regressions of bank deposit sensitivities on bank and time-series controls for 5 hiking cycles. The dependent variable is the ratio of deposit rates to the fed funds rate, B^R. Bank controls are as of the quarter immediately prior to the first rate hike. Column (2) includes date fixed effects, Column (3) includes date and bank fixed effects, and (4) excludes deposit growth. Standard errors are clustered by date and bank. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	B^R			
	(1)	(2)	(3)	(4)
Dep. rate/f^{5-10} (%)	0.53***	0.55***	0.46***	0.45***
	(0.03)	(0.06)	(0.04)	(0.04)
Deposits/Account ($ '000s)	0.09***	0.08***	0.08***	0.10***
	(0.01)	(0.02)	(0.02)	(0.02)
NIB share (%)	-0.16***	-0.15***	-0.10***	-0.18***
	(0.02)	(0.02)	(0.02)	(0.02)
Small acct. share (%)	-0.10**	-0.10**	-0.11***	-0.13**
	(0.03)	(0.03)	(0.02)	(0.04)
MMDA share (%)	0.09***	0.09***	0.06**	0.11***
	(0.01)	(0.01)	(0.02)	(0.02)
Deposits/Branch ($ mm)	0.02**	0.02***	0.03***	0.01
	(0.00)	(0.00)	(0.00)	(0.01)
Deposit growth (%)	0.27**	0.28*	0.25**	
	(0.09)	(0.11)	(0.06)	
ln(Cycle length)	12.80***			
	(2.27)			
ln(ff_T) (%)	9.36***			
	(0.60)			
Observations	30085	30085	26360	30088
Adj. R^2	0.62	0.62	0.72	0.56
Fixed Effects	None	Time	Bank & Time	None
Y mean	29.76	29.76	29.04	29.75

and time-varying factors, $\mathbf{Z}_t$, for each quarter. For the time-varying factors we assume a constant cycle length of 12 quarters and an ultimate fed funds rate equal to the risk-neutral forward rate at the 5- to 10-year horizon, f_t^{5-10}. The 12 quarter cycle is the upper quartile of cycle lengths in the estimation sample and the forward rate captures the expected level of rates to which the beta will apply. Last, we assume deposit growth is equal to our assumed drawdown rate (δ), 5%.For the variable *Dep. rate/*f^{5-10} we seed the regression with a ratio that is scaled by the maximum of f^{5-10} or the fed funds rate. We do this to accommodate declining rate environments that are not in the regression estimates. When the long-rate is falling but the fed funds rate is unchanged, the unadjusted variable goes up and mechanically

Figure IA21. Deposit sensitivity and deposit growth. This figure plots a bin scatter of the ultimate deposit sensitivity (B^R) versus bank annual deposit growth over thecycle conditional on the control variables in Table IA13 Column (2). Bins are data-driven as per Cattaneo et al. (2024).



predicts higher future betas until the fed funds rate begins to fall. Scaling by the maximum of the fed funds rate and the forward rate produces more credible estimates by attenuating the impact of these transient conditions on our betas. The implied betas are bounded in the range 0 to 125, inclusive.

$$\beta_{i,t} = \widehat{B_{i,t}} = \hat{\alpha} + \widehat{\mathbf{\Gamma}}\mathbf{X}_{i,t} + \widehat{\lambda}\delta + \widehat{\mathbf{\Theta}}\mathbf{Z}_t, \tag{19}$$

Our beta estimates are based on a hedonic regression fitted to five specific dates. To ensure the resulting estimates are valid more generally, we test whether our long-term betas are able to predict actual future betas in the overall sample. In doing so, we consider two sources of potential error: first, our estimates assume a 5% drawdown rate for deposits which is lower than the typical growth rate and, second, we generate expected betas using forward rates which may deviate from actual realized fed funds rates. The former biases our beta estimates downward relative to realized betas. The latter introduces time-series errors based deviations between the realized fed funds rate and the historical expectation implied by forward rates. We account for both in our analysis.

We estimate a regression of current deposit sensitivities, $B_{i,t}$, for each bank-quarter on 5-year lagged estimates, $\widehat{B_{i,t-20}}$,

$$B_{i,t} = \alpha + \rho\widehat{B_{i,t-20}} + \psi g_{i,t} + \chi e_t + \varepsilon_{i,t}. \tag{20}$$

We control for the difference between actual deposit growth and our assumed rate of -5%, $g_{i,t}$. We also control for the deviation of the fed funds rate from the expected rate implied by forwards, e_t. We restrict our sample period to quarters where the fed funds rate is greater than 1.75%, as forward rates are always higher than this level. A well predicted beta should have a coefficient, ρ, close to one and a constant indistinguishable from zero. Standard errors are clustered by date and bank.

The regression results in Table IA14 show our beta estimates strongly correspond with realized betas with minimal bias. In Column (1), estimated betas closely correspond to actual betas with a coefficient of 0.94. As expected, our estimates are biased downward as indicated by a constant of 4.61. The R-squared of 37% implies projected betas explain a sizable fraction of the variation in actual betas. When we include deposit growth and the rate deviation, columnc (2), we continue to find a strong correlation with our estimate but the constant is immaterial and statistically insignificant. When the growth is equal to our drawdown rate ($g_{i,t} = 0$) and the forward rate correctly predicts the fed funds rate ($e_t = 0$), our long-term betas closely predict actual betas without bias.

Table IA14: Regression: Realized betas on predicted betas. This table reports the estimated coefficients from regressions of deposit betas on lagged estimates of deposit betas. The dependent variable is the ratio of deposit rates to the average fed funds rate in the quarter. The projected beta, $\widehat{B_{i,t-20}}$, is the five-year lagged estimate. Column (2) includes the difference between each bank's deposit growth and the -5% drawdown rate, $g_{i,t}$ and the difference between the five-year risk neutral forward rate from $t-20$ and the fed funds rate at time t, e_t. Deposit growth is the log growth in deposits from $t-20$ to t winsorized at the 5th/95th levels. We restrict the sample to bank-quarter observations where the fed funds rate exceeds 1.75% as all forward rates beyond five years are above this level. Standard errors are clustered by date and bank. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	$B_{i,t}$	
	(1)	(2)
$\widehat{B_{i,t-20}}$	0.94***	0.93***
	(0.06)	(0.05)
$g_{i,t}$		0.38***
		(0.06)
e_t		2.71**
		(1.19)
Constant	4.61***	1.38
	(1.55)	(1.79)
Observations	261540	261540
Adj. R^2	0.37	0.43
Y mean	32.21	32.21

C.4 Foreign demand deposits

Foreign demand deposits are infrequent in the sample ($\sim$ 1% of observations and $\sim$ 2% of banks). Nevertheless, we develop a simple model of foreign deposit rate sensitivities using a similar approach as to what we did for demand deposits in Table IA13. Given the smaller sample we use fewer explanatory variables.

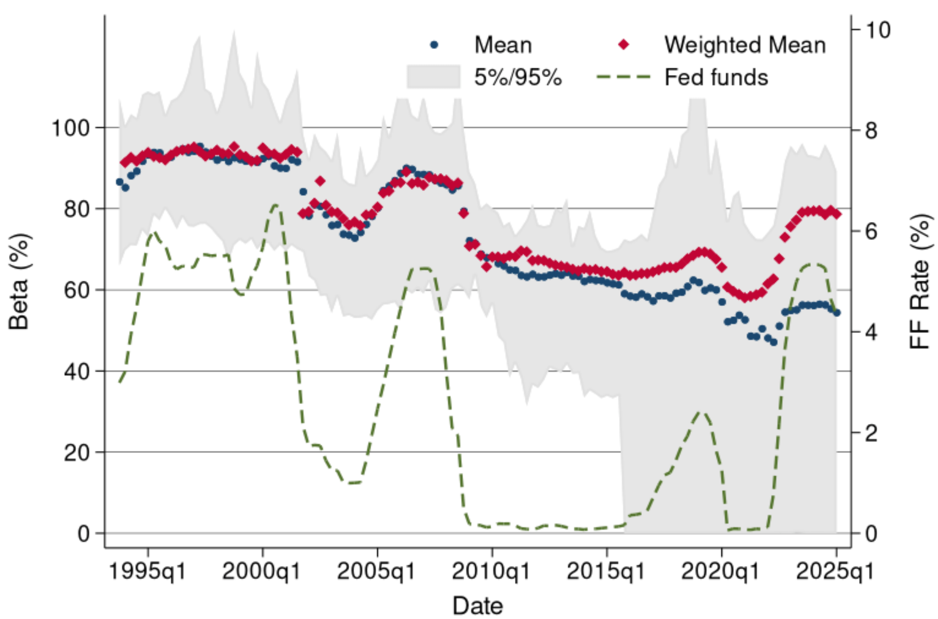
Table IA15: Summary statistics for estimates of foreign deposit rate sensitivities. This table reports the summary statistics for the variables used to estimate foreign demand deposit sensitivities over a hiking cycle. Deposit sensitivities are as of the end of a hiking cycle whereas bank controls are as of the beginning of the cycle. Control variables with extreme skewness are winsorized. *Dep. rate/*f^{5-10} is the deposit rate divided by the risk-neutral forward rate at the 5-10 year horizon as of the start of the hiking period. *ln(Liquidity/Deposits)* is the log of the ratio between cash and securities and total deposits winsorized at the top 100bps.

	N	Mean	Med.	SD	Min	Max
Deposit sensitivities						
B^R: Ratio (%)	347	84.05	88.40	37.19	0.00	282.08
Bank controls						
Dep. rate/f^{5-10} (%)	347	65.29	66.74	46.26	0.00	200.43
NIB share (%)	346	7.27	0.00	19.10	0.00	100.00
Time-series controls						
$\ln(ff_T)$ (%)	347	1.69	1.79	0.27	0.87	1.87
f^{5-10}	347	3.66	3.83	0.59	2.73	4.42

Table IA16: Regression: Foreign deposit sensitivities in hiking cycles. This table reports the estimated coefficients from regressions of bank foreign deposit sensitivities on bank and time-series controls for 5 hiking cycles. The dependent variable is the ratio of foreign deposit rates to the fed funds rate. Bank controls are as of the first quarter of each hiking cycle. Column (2) includes time fixed effects. Standard errors are clustered by date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)
Dep. rate/f^{5-10} (%)	0.26**	0.18***
	(0.08)	(0.02)
NIB share (%)	-0.70***	-0.62**
	(0.14)	(0.16)
$\ln(ff_T)$ (%)	8.90	
	(8.11)	
Observations	346	346
Adj. R^2	0.33	0.36
Fixed Effects	No	Time
Y mean	83.99	83.99

Figure IA22. Estimated long-term foreign betas. This figure plots the distribution of implied foreign demand deposit betas at a five-year horizon conditional on a 5% deposit drawdown rate. The figure also includes the 5-year risk neutral forward rate.



D Noninterest expense

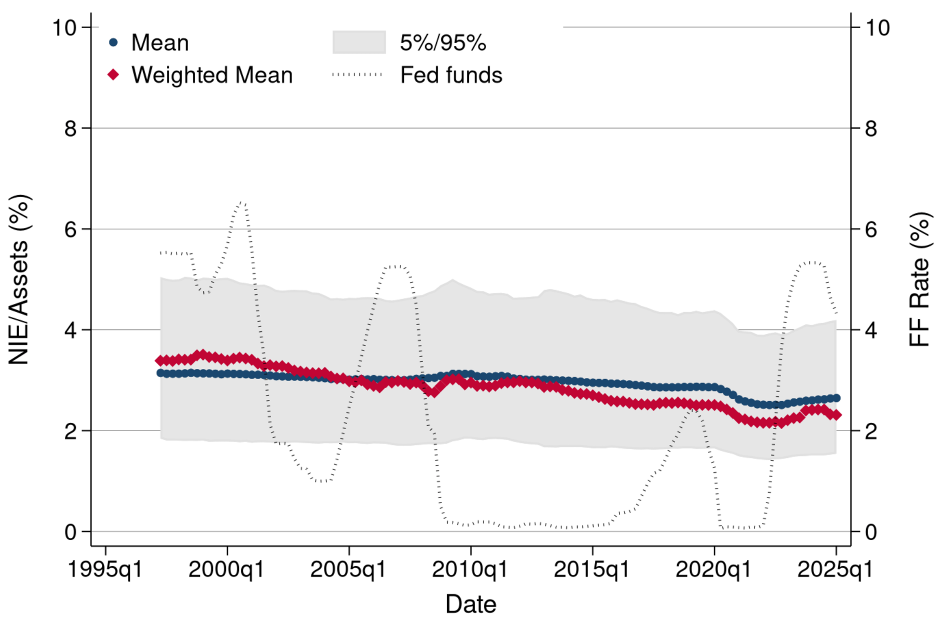
As with deposits, we incorporate the expense perpetuity, Equation 5, into a valuation equation that includes the slope of near term discount rates. The present value of expenses per dollar of assets:

$$NIE_{i,t} = \sum_{k=1}^{5} \frac{c_{i,t}(1-\delta)^{k-1}}{(1+y_k^D)^k} + \left(\frac{1-\delta}{1+y_5^D}\right)^5 \frac{c_{i,t}}{f_{5-10}+\delta}, \tag{21}$$

where t is the quarter and k is the time horizon. The forward rate, f is inferred from the discount rate, y, at specific time horizons, including the 5 to 10 year horizon, f^{5-10}. The PV-per-dollar, NIE, is then multiplied by the book value of assets to obtain the present value in dollars.

For the discount rate, we treat these off-balance sheet expenses similar to subordinated debt, using GSW yields plus the AAA spread. The drawdown rate is determined by the weighted average drawdown rate of demand deposits (5%) and loans, respectively. We do not allow the loan weighting to imply a drawdown rate faster than 20% per annum. The final estimates range from 5-20% and average around 12%. We describe the estimation of necessary expenses, $c_{i,t}$, below.

Figure IA23. Noninterest expenses relative to assets over time. This figure plots the distribution of the ratio of NIE to assets gross of loan loss reserves. The figure also includes the fed funds rate.



D.1 Necessary expenses

Our objective is to estimate the necessary expenses a typical bank must expend to retain their deposits and maintain the firm as an ongoing concern. Ideally, we would have a breakdown of fixed and variable costs for each bank's lines of business. However, given data constraints we rely on a hedonic regression to imply necessary expenses that reflect bank-specific characteristics. To do so, we estimate costs relative to assets as a linear function of time fixed effects and bank characteristics,

$$NIE_{i,t} = \alpha_t + \beta \mathbf{X}_{i,t} + \beta \mathbf{Z}_{i,t-4} + \varepsilon_{i,t}, \tag{22}$$

where $NIE_{i,t}$ is the last twelve months (LTM) average ratio of noninterest expense relative to assets (gross of loan loss reserves). The denominator, $\overline{Assets}$, is calculated as the average rather than the end of period. Revenue variables, $\mathbf{X}_{i,t}$, are also LTM relative to average assets. Other bank controls, $\mathbf{Z}_{i,t-4}$ include balance sheet variables that reflect stocks rather than flows; they are lagged four quarters and scaled by the same average assets, $\overline{Assets}$.

Table IA17 summarizes the the regression variables. To reduce the influence of outliers on our estimation, we set a floor for the NIE ratio on the left at 25bps (which is less than the first percentile) and winsorize at the 99th percentile. For other revenue ratios we winsorize at the top and bottom 50bps. To limit the impact of material acquisition/divestiture activity which does not reflect banks' ongoing expenses, we exclude bank-quarters from estimation that exhibit large changes in growth over the past year ($+/-20\%$) which reduces the sample size by roughly 11%.

Table IA18 contains the coefficient estimates from the expense regression. We find that expenses are positively relate to all forms of income in the cross-section of firms, but negatively related to interest expense. Hence business mix is important to banks expense structure. In addition, banks with high funding costs tend to expend less in noninterest expenses, consistent with some substitution between these two categories that relates to the composition of funding. Expenses are also positively related to demand deposit levels, branch network size, fixed assets, loans and loan loss reserves. There is also evidence consistent with with returns to scale as noninterest expense is lower for larger banks. While we considered several alternatives, including time- and size-varying coefficients, the results were not materially different and so we rely on this parsimonious approach.

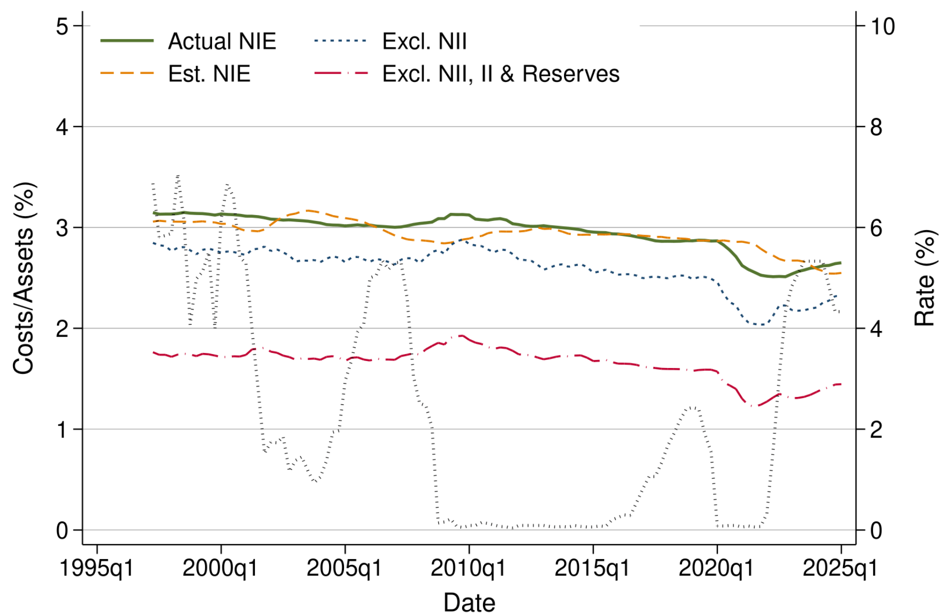
We use the empirical model to generate a standardized prediction of a bank's necessary expenses based on their underlying characteristics (see Figure IA24). We seed noninterest income (excl. deposit fees) and income from sales to zero to remove expenses related to fee-based franchises and one-time events. This adjustment lowers projected expenses by 35bps on average and is consistent with the exclusion of these revenues from economic capital calculations. We also seed our prediction with an interest income variable that is equal to interest expense; in other words, we set the bank's net interest income to zero. Given we assume loan returns cannot exceed their discount rate at origination (see discussion in Section 3.2.1)., we view it as appropriate that banks do not incur expenses related to the excess returns on loans. For similar reasons, we set expenses associated with loan loss reserves to zero. The adjustments to interest income and loans lower expenses by 95bps on average. For all other right hand side variables, we use observables at time t to generate a necessary

Table IA17: Summary statistics for estimates of noninterest expense. This table reports the summary statistics for the variables used to estimate necessary noninterest expense for the period 1997:Q2 to 2005:Q1. Income statement variables are the LTM average relative to assets gross of loan loss reserves. Deposit controls and balance sheet controls are lagged four quarters and scaled by the average assets used to scale income/expense items. *Interest Inc.* is interest from all sources. *Interest Exp.* is interest expense from all sources. *Other NII* is noninterest income excluding income from securities sales and fees from deposits. *Inc. from sales* are one time gains/losses from the sale of loan/securities. *Deposit fees* is fee income from deposit accounts. *Non-IB deposits* are non-interest-bearing deposits. *IB deposits* are interest-bearing deposits. *Branches* is the number of branches (times 100). *Fixed assets* is the fixed asset balance. *Loans* is the balance of loans net of reserves. *Loss Reserves* is the balance of loan loss reserves. *Cash & Securities* is the balance of highly liquid assets including IB balances (such as reserves), NIB balances, and securities. *log(Assets* is lagged log of assets in 2017 dollars.

	N	Mean	Med.	SD	Min	Max
NIE/Assets	595,873	2.93	2.80	0.98	0.25	9.57
Income controls (/Assets)						
Int. Inc.	595,873	5.29	5.07	1.57	1.29	13.83
Int. Exp.	595,873	1.67	1.41	1.21	0.02	5.53
Other NII	595,873	0.39	0.25	0.63	-0.13	15.48
Inc. from sales	595,873	0.07	0.00	0.35	-1.57	10.18
Deposit fees	595,873	0.30	0.24	0.24	0.00	1.74
Deposit controls (/Assets)						
Non-IB dep.	597,975	14.41	12.65	9.74	0.00	100.00
IB dep.	597,975	66.91	67.87	10.16	0.00	100.00
Branches	595,873	0.24	0.21	0.16	0.00	3.30
B/S controls (/Assets)						
Fixed assets	597,975	2.02	1.46	5.93	0.00	100.00
Loans	597,975	59.87	61.58	14.51	0.00	100.00
Loss Reserves	597,975	1.23	0.80	5.89	0.00	100.00
Cash & Securities	597,975	29.73	27.31	15.63	0.00	100.00
Other controls						
log(Assets)	597,975	5.64	5.41	1.23	3.91	15.16

expense ratio for each bank-quarter. Finally, we subtract deposit-based fee income from this estimate as these are fees the bank is likely to continue to collect if it remains an ongoing concern and we bound these estimates at a minimum of 25bps and a max of 3% (overall these bounds impact <1% of estimates). The distribution of estimates over time is depicted

Figure IA24. Expenses under varying assumptions. This figure plots the average level of noninterest expenses and predictions of costs under a variety of assumptions. Costs are reported relative to assets gross of loan loss reserves. The figure includes actual noninterest expenses, expenses predicted by the regression in Table IA18, predicted expenses where other noninterest income (NII) and income from sales are zero, and predicted expenses where other NII and gains from sale are zero, interest income is equal to interest expense, and loan loss reserves are zero. This last formulation is what we use for necessary expenses. The figure also includes the fed funds rate.



in Figure 4a.

Table IA18: Regression: Noninterest expenses relative to assets. This table reports the estimated coefficients from regression of NIE on bank controls and date fixed effects. The dependent variable is the LTM ratio of NIE to assets gross of loan loss reserves. Controls are described in Table IA17. Standard errors are clustered by entity and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

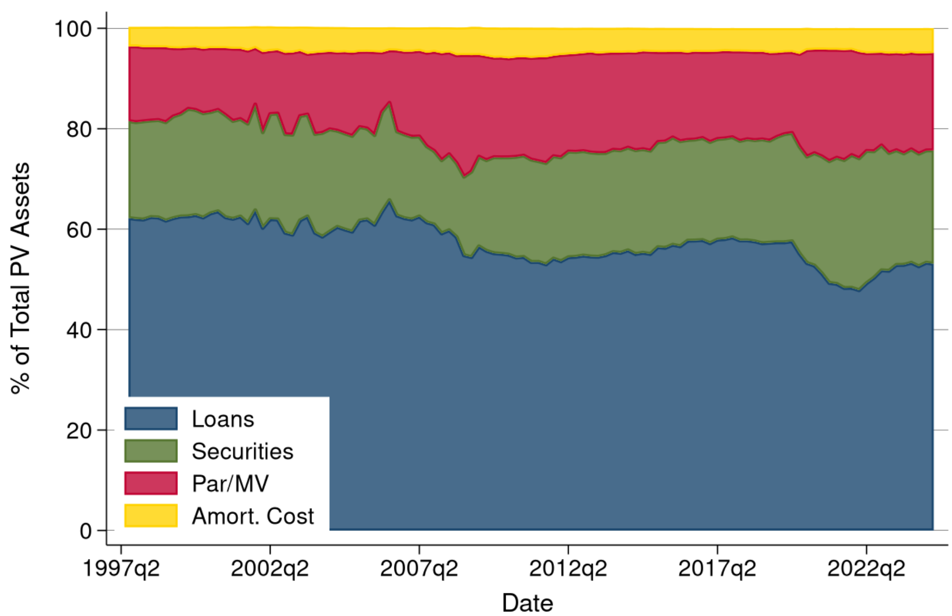
	(1)
Int. Inc.	0.22***
	(0.02)
Int. Exp.	-0.31***
	(0.02)
Other NII	0.67***
	(0.02)
Inc. from sales	0.79***
	(0.03)
Deposit fees	0.86***
	(0.04)
Non-IB dep.	0.01***
	(0.00)
IB dep.	0.01***
	(0.00)
Branches	0.80***
	(0.06)
Fixed assets	0.14***
	(0.01)
Loans	-0.00***
	(0.00)
Loss Reserves	0.16***
	(0.02)
Cash & Securities	-0.01***
	(0.00)
log(Assets)	-0.08***
	(0.01)
Observations	595873
Adj. R^2	0.63
Y mean	2.93

E Estimated Present Values

E.1 Assets

We combine the loan portfolio valuations from Section 3.2 with appropriate valuations for other assets, including securities, cash, cash equivalents, and fixed assets. Figure IA25 presents the shares of aggregate industry values of each of these components over time. The loan portfolio is by far the largest share of assets, but its share has decreased over time as securities and reserves have grown.

Figure IA25. Composition of asset values over time. This figure combines the estimated loan values with other assets values to summarize the plots the composition of industry asset values from 1997:Q2 to present. Loans reflect the estimated present value of HFI loans and the value of HFS loans. Similarly, securities is the sum of AFS and the market value of HTM as reported in the Call Report. Fair Value includes assets booked at par or market value (excluding HFS loans and AFS securities) as well as the fair value of mortgage servicing rights. Book includes line items for which the book value is used (See Table 1).

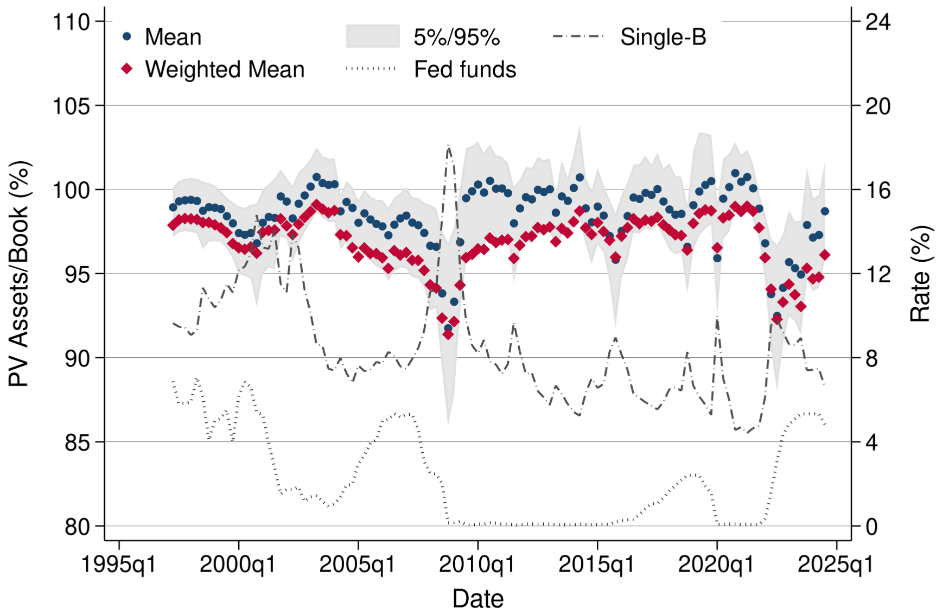


Similar to loans, the present value of assets is quite close to the book value, with the largest declines during the GFC and the recent rate hike period, Figure IA26. Unlike loan valuations, however, asset valuations for large banks tend to be lower than those for smaller banks outside these episodes. The lower valuation for large banks reflects a higher level of intangible assets in their book assets which we do not include in our estimates of present value (see Table 1).

E.2 Liabilities

Figure IA27 shows the evolution of the distribution of the present value of balance sheet liabilities scaled by total assets. On average, the value of liabilities equal just under 80

Figure IA26. Distribution of asset values over time. This figure depicts the distribution of the present value of assets relative to the book value of assets (gross of reserves) from 1997:Q2 to present. The figure includes the BB-B yield and the fed funds rate. The chart includes the 5th-95th percentile range, the average and the weighted average for each quarter.



percent of assets prior to the Global Financial Crisis and has declined since that period. Liability values for larger banks tend to increase relative to smaller banks during periods of higher interest rates, reflecting the greater sensitivity of their deposit rates to interest rates, Figure 2. Overall, however, the pattern of declining liability values relative to total assets holds for both larg and small banks.

Figure IA28 shows the distribution of the combination of liabilities and necessary expenses over the sample period. The pattern over time is similar to that for liabilities alone, however the average bank now has higher liability values than the weighted average, particularly during periods of low rates, reflecting the higher level of costs for smaller banks.

Figure IA29 summarizes the impact of depositor behavior on the value of liabilities both with and without necessary expenses. The present value of liabilities is higher when uninsured deposits reprice. The difference from typical depositor behavior, Figure IA29a, is particularly strong for larger banks later in the sample. Weighted average values vary between 80 and 90 percent of asset values excluding necessary expenses, as compared to a range of 70 to 80 percent when those depositors are assumed to remain stable. The net result is that greater reliance on uninsured deposits offsets the scale benefits larger banks enjoy with respect to expenses, Figure IA29b.

Figure IA27. Distribution of liability values. This figure plots the implied distribution of liabilities from 1997:Q2 to present. The figure includes the 5th-95th percentile, the average and the weighted average by quarter as well as the five-year risk neutral yield and the fed funds rate.

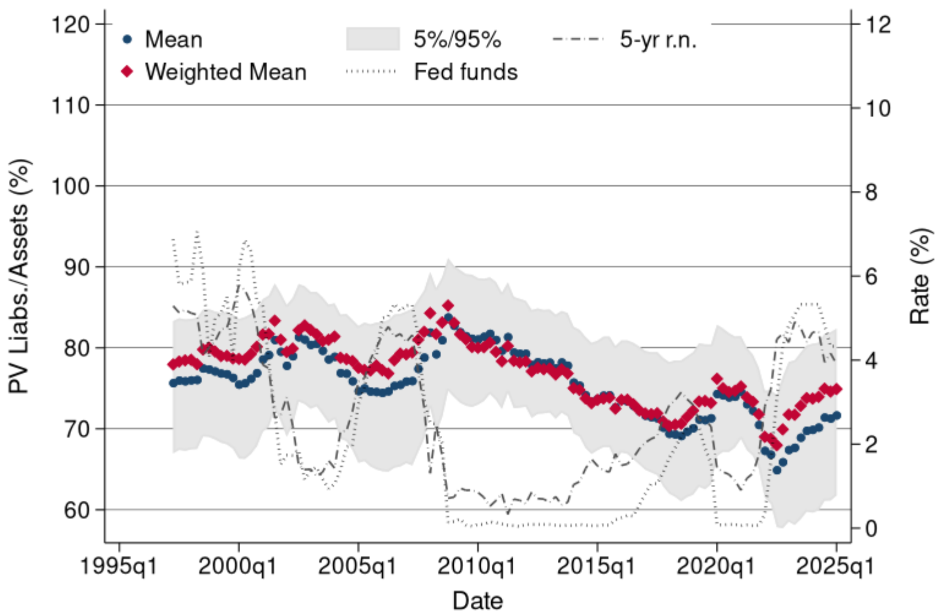


Figure IA28. Distribution of liability values including necessary expenses. This figure plots the implied distribution of liabilities to total assets, where the present value of necessary expenses are included as an additional liability, from 1997:Q2 to present. The figure includes the 5th-95th percentile, the average and the weighted average by quarter as well as the five-year risk neutral yield and the fed funds rate.

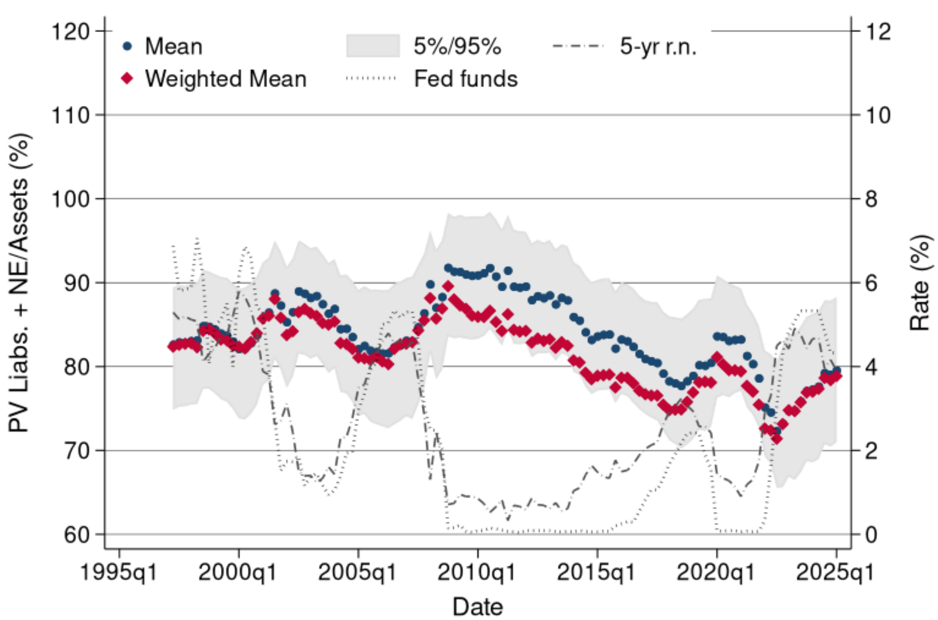
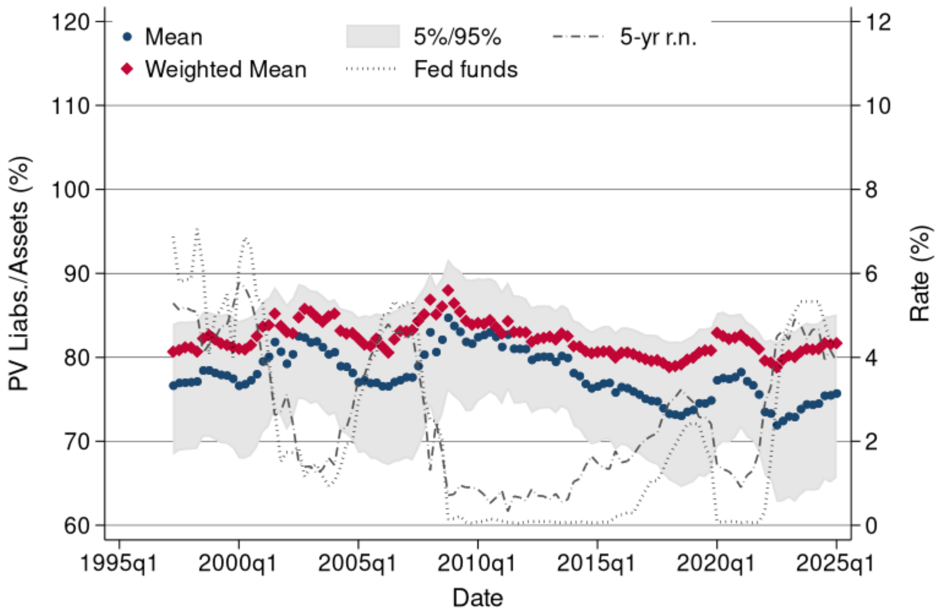
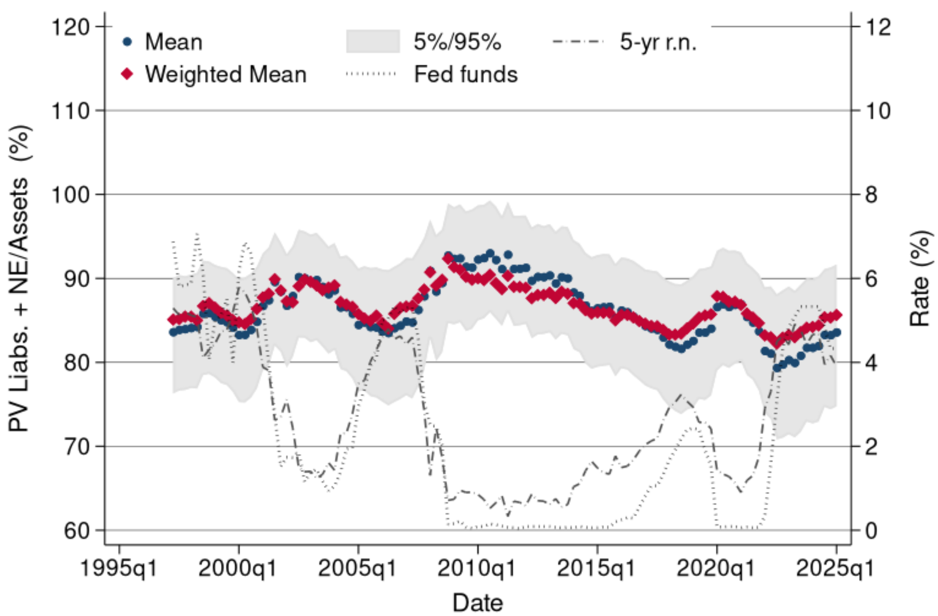


Figure IA29. Distribution of liability values under an uninsured deposit run. This figure plots the implied distribution of liabilities from 1997:Q2 to present assuming that deposit betas are one for uninsured depositors. Figure IA29a depicts the present value of liabilities to total assets. Figures IA29b adds the present value of necessary expenses as an additional liability. Each chart includes the 5th-95th percentile, the average and the weighted average by quarter. The figures also include the five-year risk neutral yield and the fed funds rate.

(a) R - PV Liab.



(b) R - PV Liab. + NE



F Validation

This section contains additional detail on the ability of EC to predict bank failure.

Figure IA30. Bank failures and bank distress over time. This figure plots the number of bank failures in our sample from 1997Q2 to present based on FDIC data. The figure also contains 'distressed' bank events that did *not* result in failure as determined by TCE (first quarter with a TCE $< 3\%$).

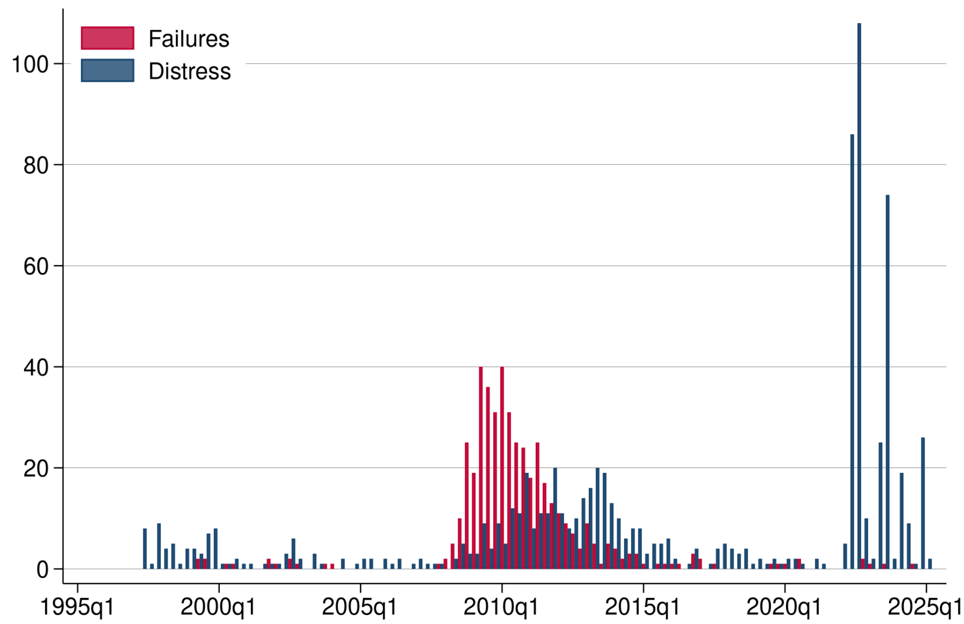
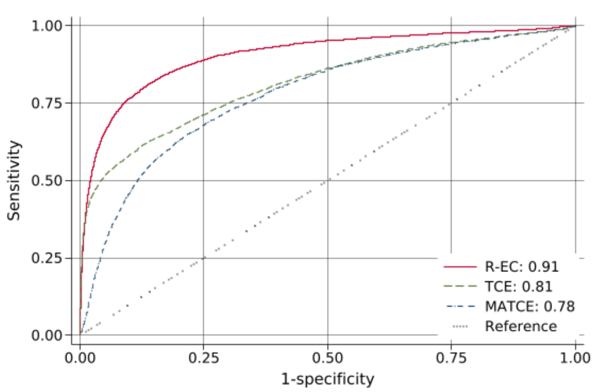


Figure IA31. Receiver Operating Curves for solvency measures: Robustness This figure plots ROCs for a variety of capital measures. ROCs are based on a logit model with a failure dummy as the dependent variable and a lagged measure of capital as the independent variable. We consider two dependent variables: a dummy equal to one if a bank fails in the next 8 quarters and a dummy equal to one if a bank fails in the next 16 quarters. Line labels also report the AUC.

(a) 8-quarter



(b) 16-quarter

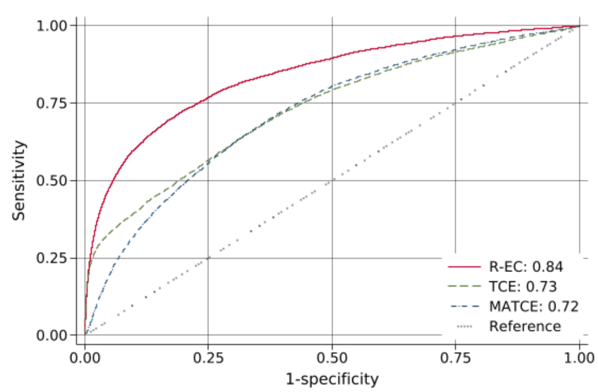


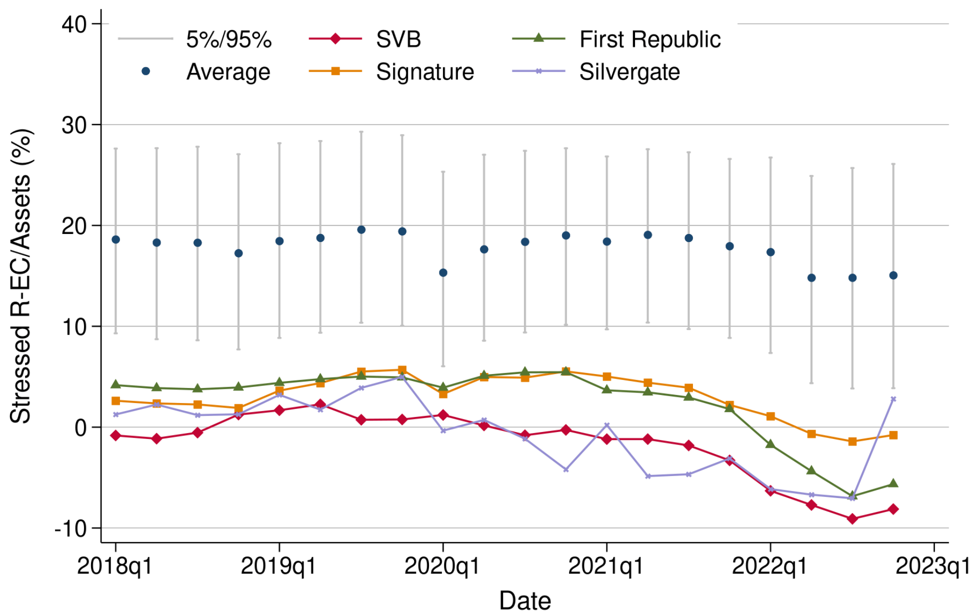
Table IA19: 2022:Q3: Economic Capital vs. Other Metrics. This table summarizes several measures of bank capital for banks that failed in 2023:Q1 as of 2022:Q3. The table reports the rank relative to banks with more than $10bn in assets as well as the level of capital to assets (in percent). Ranks are reported from low to high. R-EC is the economic capital in a deposit run scenario. TCE is the tangible common equity of the bank, and MATCE is TCE less the difference between book and mark-to-market assets where the MTM assets are based on our PV estimates.

	R-EC		EC		TCE		MATCE	
	Rank	%	Rank	%	Rank	%	Rank	%
Silicon Valley	1	-2.84	7	13.65	49	7.06	37	-1.30
Silvergate	2	-1.21	54	22.55	58	7.28	117	4.43
First Republic	3	0.37	6	13.45	37	6.47	14	-3.02
Signature	4	1.88	18	16.45	28	6.10	102	3.05
Industry (> $10b)	69.50	12.15	68.92	22.86	68.25	7.60	67.50	0.90

Table IA20: 2021:Q4: Economic Capital vs. Other Metrics. This table summarizes several measures of bank capital for banks that failed in 2023:Q1 as of 2021:Q4. The table reports the rank relative to banks with more than $10bn in assets as well as the level of capital to assets (in percent). Ranks are reported from low to high. R-EC is the economic capital in a deposit run scenario. TCE is the tangible common equity of the bank, and MATCE is TCE less the difference between book and mark-to-market assets where the MTM assets are based on our PV estimates.

	R-EC		EC		TCE		MATCE	
	Rank	%	Rank	%	Rank	%	Rank	%
Silvergate	1	2.37	49	21.93	103	9.62	119	9.62
Silicon Valley	2	3.21	20	18.83	16	6.95	63	6.34
Signature	3	4.24	15	18.21	2	6.02	55	6.12
First Republic	10	8.37	30	20.15	9	6.65	83	7.15
Industry (> $10b)	69.45	13.78	68.70	22.58	68.58	8.67	67.12	6.45

Figure IA32. R-EC with interest rate stress: 2018:Q1 - 2022:Q4 This figure plots R-EC relative to assets assuming that risk-free yields at all horizons increase by 200bps. The plot includes the measure for four banks that failed in March of 2023 as well as the mean and 5th-95th percentile ranges for the banking sector.

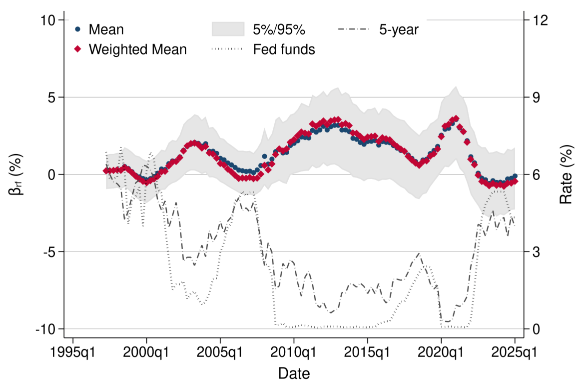


G Applications

G.1 Exposure to shocks

Figure IA33. Distribution of interest rate risk over time. These figures plot the distribution of interest rate risk, β_{rf}, from 1997:Q2 to present. Figure IA33a depicts the change in EC for a 100bps shock in interest rates. Figure IA33b depicts the change in R-EC. The rates vary due to the deposits taking on a different duration when uninsured deposits have a beta of one. Each chart includes the 5th-95th percentile, the average and the weighted average as well as the single-B yield and the fed funds rate.

(a) EC



(b) R-EC

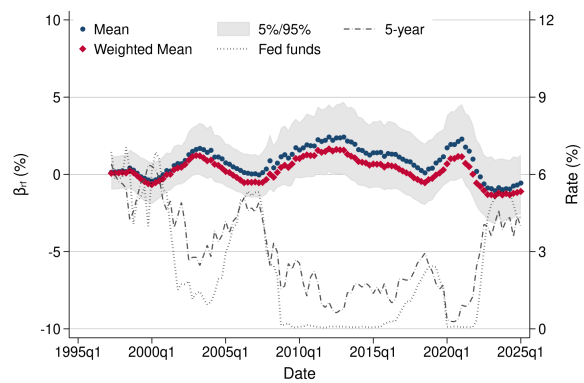


Figure IA34. Distribution of credit risk over time. These figures plot the distribution of of how EC and R-EC change in response to a 100bps change in AA credit spreads from 1997:Q2 to present. Sensitivity to spreads ranges depending on the underlying risk premium. Each chart includes the 5th-95th percentile, the average and the weighted average as well as the single-B yield and the fed funds rate.