STAFF REPORTS

NO. 1144
MARCH 2025

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FEDERAL RESERVE BANK of NEW YORK

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Federal Reserve Bank of New York Staff Reports, no. 1144
March 2025
https://doi.org/10.59576/sr.1144

Abstract

Conventional measures of bank solvency fail to account for the unique liquidity risks posed by deposits. Using public regulatory data, we develop a novel measure, economic capital, that jointly quantifies the impact of credit, liquidity, and market risk on bank solvency. We validate that economic capital is a more timely and accurate indicator of bank health than standard solvency measures. Using our framework, we examine the evolution of banking sector risk exposures over several decades. Despite significant reforms in the aftermath of the Global Financial Crisis, economic capital suggests that liquidity and market risks have grown and remain elevated.

JEL classification: G21, G17, G01
Key words: bank capital, solvency, liquidity, financial stability

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1 Introduction

Banking sector distress, with its direct implications for credit provision, is considered a key contributor to the length and severity of business cycles (e.g., Bernanke, 2023), hence assessments of bank solvency are central to the monitoring and regulation of banks. The most prevalent measures of bank health referenced by market participants and regulators are capital metrics grounded in accounting rules. Underlying these rules is the notion that the bank will remain a "going concern" and therefore differences in the timing of payments do not impact bank solvency. As a consequence, standard measures of bank capital fail to incorporate the inherent fragility posed by demand deposits and their implications for bank survival (Diamond and Dybvig, 1983).

In this paper, we develop an alternative approach to measuring bank capital that bridges the gap between current capital metrics and the liquidity risks highlighted by the banking literature. Our approach nets the present value of bank assets and liabilities, thereby relaxing the assumptions embedded in conventional capital measures by incorporating the expected timing of payments. Doing so allows us to explicitly condition on the extent of depositor withdrawals when calculating bank capital. The resulting measure is able to jointly quantify the impact of credit losses, funding liquidity, and market conditions on bank solvency. In this way, we present a unifying approach to assessing the stability of the banking sector that we show is more forward-looking, more timely, and more comprehensive than current methods.

Banking theory highlights the fragility of banks due to their unique capital structure that funds investments in risky, illiquid assets using demandable debt (i.e., deposits). In these frameworks, depositors may withdraw their funds if they are concerned that asset values are insufficient, thereby requiring banks to replace the deposit funding or to sell assets. Asset values may precipitate withdrawals because they vary with economic conditions (Goldstein and Pauzner, 2005), such as loan performance (Fisher, 1911) or interest rates (Drechsler et al., 2023; Haddad et al., 2023; Luck et al., 2023; Curti and Gerlach, 2024). These withdrawals can further impair the bank due to the need to replace deposits with more costly funding or the need to sell inherently illiquid assets like loans (Diamond and Dybvig, 1983). However, accounting-based measures of bank capital do not reflect the relevant value of assets to depositors nor do they consider the exposure of bank funding to depositor behavior. As a result, the well established theoretical interactions between solvency and liquidity are often overlooked in practice where these risks are treated as distinct – credit losses, interest rate risk, and funding liquidity are evaluated separately using methods that are not quantitatively comparable.[1]

To address this gap, we develop a comprehensive measure that we label "economic capital", or EC, which is based on the net present value of bank assets and liabilities. We estimate the present value of assets in this calculation to reflect their *financeable* value rather than their liquidation value which may be subject to additional impairment. Hence, estimates of market value are our primary indicator of asset values as they indicate the value available to service liabilities at a particular point in time.[2] For the present value of liabilities, we assume that they are risk-free with no expectation of default — treating liabilities as risky would increase capital estimates by valuing the bank's default option. On net, economic capital approximates the value available to creditors less the value of funding obligations assuming they are repaid in full.

EC can be sensitized to depositor behavior by assuming uninsured deposits withdraw, effectively accelerating the timing of liability payments. If the bank has sufficient capital in the depositor withdrawal scenario, it indicates that it has the necessary value to replace withdrawn deposits and still be viable. However, if the bank appears poorly capitalized in this scenario, it suggests the bank may have insufficient value and the bank must either pay a risk premium for funds or sell assets that may be illiquid; both of which would further impair economic capital and by extension the solvency of the bank. Our notion of economic capital is designed to capture the distance to this tipping point where banks shift from being able to replace funds at risk-free rates and where uninsured depositors become concerned that they will suffer losses.

A key challenge in calculating economic capital is that it diverges from reporting conventions. Markets and regulators primarily rely on bank filings that are constructed using standard accounting practice which records "book" values rather than market (i.e., fair) values. Hence, there is a significant gap between the data that is reported and the values needed to construct economic capital. In part, this reflects the challenge of valuing financial instruments that are not typically traded, like loans, or depend on counterparty behavior, like demandable debt or callable securities. To overcome this, we develop several methods to estimate present values using publicly available regulatory data for U.S. commercial banks. The three estimated categories of EC are (i) the value of portfolios with fixed rate instruments, (ii) the value of demand deposits, and (iii) the value of necessary operating

[1]For instance, capital metrics that incorporate credit losses rely on the book value of assets and liabilities. Interest rate risk is evaluated using market values that are not comparable to measures of capital. And, liquidity measures like the Liquidity Coverage Ratioo (LCR) and Net Stable Funding Ratio (NSFR) focus on operational liquidity (i.e., the speed with which an asset can be liquidated or a liability can withdraw) regardless of the bank's solvency.

[2]We do not apply haircuts to market value at this time. Applying haircuts, like those used by the discount window, further impairs loan values relative to other assets.

expenses.

The value of portfolios with fixed-rate instruments, which include both assets, such as loans, and liabilities, such as time deposits and long-term debt, varies over time with interest rates, credit spreads, and credit losses. We develop a methodology that estimates innovations in these values using reported book values and the maturity structure of these portfolios. For loans, we incorporate estimates of prepayment behavior to capture the significant convexity in high duration portfolios and we assign bank-specific, time-varying credit spreads using implied interest rates on individual bank loan portfolios.

For demand deposits, we take a discounted value approach that estimates their value as a function of their interest rate sensitivity (i.e., beta) and a common drawdown rate. We take a novel approach to estimating long-horizon betas for discounting purposes that vary both over time and in the cross-section of banks. To do so, we use historical tightening cycles to inform beta estimates that are conditional on market conditions, deposit growth, and proxies for depositor composition. This deviates from standard practice that relies on near-term betas or product-specific betas that are constant over time and across banks. Our approach results in material variation in deposit values across banks and within banks over time.

For expenses, we estimate the minimal expense necessary for a bank to continue as an ongoing concern such that they recover the value of their assets and maintain the level of their liabilities. A firm must incur costs to provide deposit services, monitor loans, and work out delinquent debts. We exclude expenses that are related to revenues that are not reflected in our present value calculations. We estimate these expenses based on bank characteristics. Again, this deviates from prior work as it allows expenses to vary in the cross-section of banks and over time in a way that reflects differences in bank business models.

There are several components of bank value that we do not include in our calculations, primarily related to off-balance sheet assets and liabilities. 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 funding based on these future cash flows. Rather, banks are restricted to secured funding based on the tangible assets they hold on their balance sheet. Second, we do not account for derivatives that might hedge banks against changes in market prices as the available public data is not sufficient to assess the state-contingent value of hedges. Also, 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 should be improved. Last, we do not consider the potential impact of off balance sheet commitments like credit lines.[3]

Using our estimates of present value we calculate economic capital from 1997 onward under standard business conditions, denoted EC, and when uninsured depositors reprice to prevailing rates rather than below market rates, R-EC. In this latter, "run" scenario, we account for changes in depositor behavior by assuming uninsured depositors are replaced at prevailing rates (i.e., the deposit beta for these deposits goes to one).[4] This assumption raises the value of liabilities and lowers capital, hence R-EC is the binding measure for evaluating bank solvency. If a bank looks poorly capitalized under R-EC, it raises the likelihood that depositors will insist on moving or repricing their commitments (Goldstein and Pauzner (2005)). R-EC can be readily stressed to a variety of shocks, including losses to specific asset classes or specific economic scenarios. We consider two scenarios to illustrate this approach: a rise in the yield curve and an increase in credit spreads.

While the levels of EC and R-EC are not directly comparable to accounting based capital metrics, we can interpret the time-series variation, cross-sectional distribution, and sensitivity to stress as relative shifts in solvency. Versus current practice, our formulation of economic capital is closest to the economic value of equity (EVE) that is commonly used to assess market risks like interest rate risk (IRR) (Basel Committee on Banking Supervision, 2015). However, in contrast to this asset-liability management framework that focuses on changes in response to rate shifts, we emphasize a *level* of capital that is constructed to reflect a buffer to creditor losses. This allows us to jointly assesses credit and liquidity risks in addition to market risks.

With our estimates in hand, we test the informativeness of our measure to validate that it has superior information content relative to typical measures of book capital. We show that the major banks that failed in March of 2023 were easily identified as poorly capitalized years in advance. More importantly, we demonstrate that R-EC is a statistically superior capital metric for predicting bank failure across a range of economic conditions from 1997 to 2024. With respect to 2023, and bank failures more generally, the improvement is primarily due to the inclusion of the present value of liabilities. One interpretation of this finding is that our market value estimates are not much better at identifying unanticipated shocks to credit losses, but that they do help reveal which banks are more sensitive to such losses given their funding mix.

Having validated that EC and its variants have relevant information, we make several

[3]The behavior of credit lines is highly heterogeneous across borrower type (Chodorow-Reich et al., 2022) and can impact both assets an liabilities. Incorporating off-balance sheet commitments would require substantial changes in how these data are reported in regulatory filings.

[4]This approach is consistent with a number of papers that have evaluated the role of uninsured deposits in the March, 2023 bank distress: Drechsler et al. (2023); Haddad et al. (2023); Luck et al. (2023).

novel observations regarding the financial stability of the banking sector over time. First, EC and R-EC indicate a modest increase in banking sector capital, respectively, in the aftermath of the Global Financial Crisis (GFC) and following the implementation of the Dodd-Frank Act (DFA). However the return to pre-GFC levels was slow, primarily due to the elevated value of liabilities when rates are low. The speed of the recovery contrasts with much more significant and rapid increases in risk-weighted capital ratios, lending credence to concerns that risk in the banking industry may have persisted despite perceived improvements in regulation efforts and book capital.Second, EC as well as accounting-based capital measures did not indicate weakness prior to the distress events of March 2023, growing from lows during the Global Financial Crisis (GFC) to robust levels in 2021-2022. However, the benefits of this growth improvement were largely illusory: exposure to uninsured depositor withdrawals, the difference between EC and R-EC, rose during this period and peaked in the quarters prior to March 2023. Third, stressing R-EC to interest rates and risk prices suggests that exposure to financial conditions was also heightened in advance of 2023. The coincidence of these risks implies the industry was increasingly exposed to a sharp change in financial conditions and that despite the level of conventional capital ratios there were growing threats to financial stability.

Our core contribution relative to the earlier literature is to provide a transparent framework through which to quantitatively examine and assess the health of banks and the banking sector. The approach can jointly assess the asset and funding liquidity of the bank to generate a measure of solvency. Further, it can readily serve as a benchmark with which to consider risks posed by specific scenarios such as those used in stress tests. In addition, we introduce a rich methodology by which we can map public regulatory data into our measure, which captures critical time series and cross-sectional differences in banks as far back as 1997. As a novel measure of bank solvency, economic capital could be used to investigate a host of important questions related to the banking sector, including the determinants of bank credit provision, the impact of monetary policy on the banking sector, and the benefit of liquidity facilities on financial stability.

Our estimates are not without important caveats. Due to gaps in the data, we rely on a number of assumptions to recover a measure of bank value. For instance, we lack details on loans, depositors, expenses, and hedges. Moreover, we cannot account for novel financial arrangements that are not easily observed in regulatory data. However, to the extent an asset or liability can be valued, it can be incorporated into our approach. Finally, our measure is for individual commercial banks, rather than for consolidated bank holding companies, so we do not capture the impact of activities in non-bank subsidiaries, such as broker-dealers, finance units, or other affiliated entities.

Several recent academic papers have assessed the impact of the 2022 to 2023 interest rate cycle on the value of bank equity. Some of these focus primarily on the asset side of the balance sheet.[5] For instance, Jiang et al. (2024) estimate market value losses on banks' loans and securities of more than $2 trillion, nearly equal to industry capitalization. Flannery and Sorescu (2023) examine the impact of unrealized losses on loans and securities on regulatory capital and find that if these losses were recognized, about half of banks would have failed to meet minimum regulatory requirements. In contrast to our measure, these papers do not take account of the impact of changes in the value of liabilities, so they present only a partial picture of the impact on economic solvency.

Recognizing the importance of deposits in bank economic value, a number of recent papers have examined the stability of the deposit franchise – or its converse, the possibility of deposit runs – during the 2023 banking turmoil and in prior periods. The models in these papers generate equilibria where depositors run, generally due to concerns about bank solvency when interest rates have risen, in ways that are consistent with the experience in March 2023 (Drechsler et al., 2023; Haddad et al., 2023; Jiang et al., 2024). These papers emphasize the role of uninsured deposits as a key indicator of run risk, as insured depositors are not exposed to default risk which mitigates their incentive to run.[6]

Our valuation of liabilities is closely tied to prior work in the literature that considers the effective maturity of bank deposits (Flannery and James, 1984) and deposit franchise values (Drechsler et al., 2021) as hedges to asset interest rate risk (IRR). Most of this literature finds that deposits hedge against losses of fixed-rate assets when interest rates rise, though DeMarzo et al. (2024) concludes the deposit franchise does not offset losses unless deposits have a defined maturity and/or operating costs are substantial. Our approach to valuing liabilities builds on methods that have been suggested for demand deposits (Sherman, 2013) and contributes to the growing work on the cross-sectional and time series variation in deposit betas (e.g., Emin et al., 2023). Our estimates of betas are the first to emphasize the importance of forward-looking valuation parameters that are conditional on deposit growth and exploit novel data to capture cross-sectional differences in deposit pricing.

[5] The capital measures generated in these papers are conceptually similar to the market-adjusted tangible common equity (TCE) measures calculated by industry analysts.

[6] Uninsured deposits play an important role in several papers that assess banks' interest rate risk exposure. For instance, English et al. (2018) find that unexpected interest rate increases are associated with declines in equity valuations and that these effects are positively related with reliance on core deposits. Abdymomunov et al. (2023) find higher interest rates increase net interest margin but reduce the EVE, especially for smaller banks. Finally, Begenau et al. (2015) find that the banking industry became more exposed to IRR from 1995 to the GFC, but that exposure has since leveled off, with much of the increase being driven by the largest banks.

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 describes our estimates of economic capital, compares EC to conventional capital measures, and tests economic capital as a predictor of bank health. Section 5 summarizes our findings.

2 Measures of Solvency

Bank regulators and supervisors, industry analysts, and researchers 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 their approaches to recognizing changes in the value of bank assets, liabilities, and off-balance sheet positions over time in response to changes in the creditworthiness of borrowers and counterparties, as well as in interest rates, credit spreads, and other market factors. Indeed, many individual measures use a mix of approaches, resulting in inconsistent treatment of different types of balance sheet positions. These inconsistencies can complicate interpretation of the resulting solvency measures.

Arguably the most widely used measures of solvency are regulatory capital ratios, 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. Deterioration in asset values due to the credit impairment of individual borrowers are recognized – for instance, via the allowance for credit losses for loans – but changes in value due to movements in interest rates and market credit spreads are generally not recognized, except for positions held in the trading or available-for-sale (AFS) accounts. On the liability side of the balance sheet, changes in value are generally not recognized for either credit or interest rate movements. Consequently, reported values of common equity and regulatory capital (e.g., Tier 1 common equity) embed a mixture of fair values, par values, and amortized costs from both sides of the balance sheet.

Given this approach, the current regulatory capital framework may not produce an accurate point-in-time assessment of banks' economic capital and solvency, especially if a bank has a significant unhedged mismatch between the duration of its assets and the duration of its liabilities. The same is true of commonly referenced accounting-based measures of bank value, such as tangible common equity (TCE), which embed many of the same valuation assumptions. While comfortably operating as a going-concern, inferences from reported "book" capital and EC might not be particularly salient; however, during times of stress, creditors are sensitive to economic solvency rather than accounting ratios. Thus, it is important to have solvency measures that do not depend solely on accounting and regulatory constructs to help identify weak banks.

A number of measures have been used by bank stakeholders to attempt to address these gaps in conventional measures. These alternatives can be broken into two broad categories: point-in-time measures that summarize current bank capital given prevailing conditions and stress values that estimate capital in response to changes in financial conditions. The simplest of the point-in-time measures incorporate mark-to-market changes in bank assets in the calculation of equity capital. These measures typically include market gains and losses on securities, but more sophisticated approaches recognize changes in the value of loans (Flannery and Sorescu, 2023; Jiang et al., 2024). In its simplest form, these measures are referred to as market-adjusted TCE, (for example, see S&P Global (2023)).

While these approaches make important adjustments to the asset side of the balance sheet, they do not incorporate the impact of market changes on liabilities, which can be substantial. This is particularly true for deposits, whose value can fluctuate significantly as interest rates or depositor behavior change. Measures that impose market values solely on the asset side of the balance sheet thus present an incomplete, and potentially misleading, perspective of banks' true economic solvency.[7]

Both researchers and practitioners have long recognized the importance of funding composition as a determinant of bank profitability (e.g., Samuelson, 1945). Since deposits typically carry below-market rates (Hannan and Berger, 1991) and have a long effective maturity (Sherman, 2013), they have economic value below their par or face value and this gap is wider the greater the gap between deposit and market rates (Drechsler et al., 2017).[8] Thus, deposits can serve as a hedge against the negative impact of rising rates on assets. Of course, this hedge depends on a bank's ability to retain its deposit base when the economic value of assets decline (Egan et al., 2017; Drechsler et al., 2023; Haddad et al., 2023; Luck et al., 2023; Curti and Gerlach, 2024).

Indeed, supervisors and risk managers developed EVE to specifically evaluate the *net* exposure of banks to interest rate risk (Basel Committee on Banking Supervision, 2015).

[7]Some argue that measures imposing market values on assets but not on deposits and other liabilities represent a "conservative" solvency measure, since any additional value coming from liabilities is omitted. However, this reasoning assumes that market values of assets are lower than book values, which need not be the case (e.g., when interest rates fall). More significantly, such measures fail to distinguish among banks with very different liability-side market sensitivities, such as those with very large or very small shares of uninsured deposits. These measures thus give a noisy signal across banks of true economic solvency.

[8]That is, a dollar of deposits has economic value of less than a dollar to depositors because of below-market deposit rates and the time value of money. Since deposits are a bank liability, this "discount" creates economic value for the bank.

EVE is nearly always used to assess potential changes in economic value rather than the level of value at a point in time. In addition, estimated changes in EVE are typically compared to regulatory or book capital rather than to the level of EVE, which could lead to biased assessments. For instance, comparing estimated changes in EVE to a level of regulatory capital would fail to distinguish between cases where a bank's economic capital was significantly below its regulatory capital and cases where economic capital excess regulatory capital. True interest rate risk exposure would be significantly higher in the first case than the second.

Other measures that assess the risk of *changes* in bank solvency include Earnings-at-Risk (EaR) and, in a slightly different setting, stress testing. EaR assesses the impact of changes in interest rates on near-term earnings over a specified horizon, typically a year. Impacts on income beyond the EaR horizon are not recognized.[9] 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 the stress test horizon.[10] Thus, stress testing as currently implemented features similar limitations as point-in-time regulatory capital ratios and EaR in that it does not capture the full impact of stress on solvency that are not incorporated into near term earnings and accounting measures.

Hence, our approach to economic capital is intended to provide an internally consistent, point-in-time measure of bank solvency that can be estimated using available data. The measure provides a single framework that can comprehensively capture the range of risks reflected in other metrics, including interest rates, credit risk, and funding risks. Since our measure is based on regulatory report data, we can construct historical estimates spanning several previous interest rate cycles, providing us with rich context for assessing the outcomes we produce and for analyzing how the banking industry's economic solvency has evolved over time.

3 Data and Methods

This section outlines our approach to measuring solvency, the data we use, its limitations, and the methods we employ to address those limitations. With respect to methods, we discuss the elements that are important for understanding valuation across banks and over time, rather than fully describing all aspects and alternative modeling choices. The Internet

[9]As a risk management measure, EaR may actually provide perverse incentives for banks simply to shift interest rate risk exposure beyond the EaR horizon, for instance by holding longer duration assets.

[10]In U.S. stress testing the stress test horizon is nine quarters.

Appendix (IA) to this paper contains a detailed description.

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 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 a risk premium, rp_t, that reflects the riskiness of the cash flows and implies a discount factor, whereas liabilities are discounted using risk-free rates. The choice of rates is designed 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 must be repaid in full and the option to default does not create value for the bank.[11]

We include the present value of certain operating expenses as a liability to capture the costs necessary to realize the value of their 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 Economic Value of Equity, or EVE, that supervisors and risk managers have traditionally used to estimate banks' exposure to interest rate risk. However, we depart from EVE in two important ways related to our objective of capturing the solvency of an institution rather than interest rate risk exposure *per se*. First, we choose discount rates and balance sheet categories to recover the capital buffer to creditor losses rather than an approximation of equity value. Second, we focus on the level of the buffer and not solely on sensitivities in response to interest rates.

3.1 Data

Our focus is to model commercial banks in a way that captures the core deposit-taking and lending activities of these firms. The primary data source we use is the Call Report (FFIEC 031/041) for commercial banks. The Call Report contains balance sheet and income state-

[11] Applying a risk premium *lowers* the value of liabilities due to a bank's potential for default.

ment information, along with a range of supplementary schedules containing additional detail about the maturity composition of loan and securities portfolios, and regulatory capital.

The Call Reports are filed quarterly by every U.S. commercial bank and some other U.S. depository institutions and are available for a comparatively long historical period, dating back into the 1980s. However, 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 2024:Q1, with some exclusions. In particular, we limit the sample to banks with more than \$50m in assets.[12] We also exclude several types of bank entities that are atypical.[13] Our final sample includes 11,601 unique institutions that represent over 90% 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 booked at fair value (i.e., market value) on the balance sheet while other items are reported at market value in supplementary schedules. In both cases, we assume the market value reflects the relevant value for the saleability or financeability of an asset. For short maturity or floating rate items, we assume the book value (i.e., par) is the same as the relevant present value. With the exception of demand deposits, we use the reported book value for these items. The remaining assets and liabilities are reported on an amortized cost basis.[14]

For balance sheet categories that include fixed-rate instruments, we exploit the maturity data available in supplementary schedules of the Call Report, which allow us to estimate the present value of instruments that are reported on an amortized cost basis. These schedules contain maturity information on residential real estate (RRE) loans, non-RRE (all other) 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.

[12] Our cut-off of \$50m is indexed to 2023 dollars using the GDP price deflator. The remaining banks represent $\sim 90\%$ of bank-quarter observations in the sample period. The smallest banks require additional assumptions to estimate bank value. For instance, banks with less than \$25m in assets file a less comprehensive Call Report prior to 2001.

[13] Specifically we drop any Call Report filers that are designated as bank holding companies, 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 as deposits for these banks have unique deposit insurance and depositor behavior. What remains are state savings banks, state member banks, savings & loans, national banks, non-member banks, federal savings banks, and cooperative banks.

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

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 make 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 assets. The magnitude of the estimated components underscores the opacity of bank solvency using current reporting standards.

Table 1: Balance sheet composition. This table summarizes the composition of the bank balance sheets in our sample from 1997:Q2 through 2024:Q1. All items are scaled by book assets. Ratios are reported based on the sample mean and in aggregate (Industry). Assets and liabilities are categorized based on our approach to obtaining present values. *Par/Fair Value* items are reported on balance sheets at par or fair value and we use those values as the present value. *Amortized Cost* items are reported at amortized cost and we either obtain fair values from the Call report, *FV Reported*; estimate them using the methodologies outlined in Sections 3.2 and 3.3, *Fixed-Rate Portfolios* or *Demand Deposits*; or, 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 detailed in IA Section A.

(a) Assets

	% of Assets	
	Mean	**Industry**
Par/Fair Value:		
IB balances	3.91	4.91
NIB balances	2.82	2.40
FF & Repo	2.62	3.86
AFS securities	18.85	15.95
Equity securities	0.20	0.17
HFS loans	0.44	1.49
Trading assets	0.04	4.83
Other	1.11	0.87
Amortized Cost:		
Fair Value Reported		
HTM securities	3.58	3.43
Mort. servicing rights	0.04	0.29
Book Value Used		
Fixed assets	1.77	1.02
Intangibles	0.42	2.00
Other	1.64	3.78
Fixed-Rate Portfolio		
HFI Loans	63.48	55.94
Loan loss reserves	-0.92	-0.96

(b) Liabilities

	% of Assets	
	Mean	**Industry**
Par/Fair Value:		
FF & Repo	1.35	5.08
Trading liabilities	0.01	2.37
Other	0.05	0.24
Amortized Cost:		
Book Value Used		
Other	0.69	2.22
Fixed-Rate Portfolio		
Sub. debt	0.03	0.96
Other debt	3.76	7.06
Time deposits	34.24	16.32
Demand Deposits		
Domestic	49.14	47.61
Foreign	0.08	8.06
Total	49.22	55.67

In addition to incorporating balance sheet items, we estimate the value of the expenses necessary to operate the bank and provide services to depositors. This off-balance sheet liability is based on Call Report and SoD data. The methodology is described in Section 3.4. For both demand deposits and necessary expenses we create empirical models that describe deposit betas and necessary expenses in the cross-section of banks. We then use these models to generate predictions for these parameters in our valuation calculations. In both cases, we abstain from fixed-effect models and we winsorize the data. Doing so allows us to estimate these variables for all banks, regardless of their history and minimizes the influence of extreme outliers. However, our approach also means that individual bank estimates may not capture atypical banks. We will test the information content of our estimates to ascertain the value of these trade-offs.

We utilize several other data sources to obtain interest rates and credit spreads to inform our discount rates. For Treasury rates at relevant maturities (one to ten years) we use zero-coupon yields as described by Gürkaynak et al. (2007), henceforth GSW. 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 yields, we use credit spreads implied by ICE Bank of America corporate bond indices.

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. Future work can assess methods of bridging our estimates to BHCs.

3.2 Portfolios with fixed-rate instruments

Banks hold and borrow using fixed-rate securities that are sensitive to shifts in discount rates. However, banks are not required to report the fair value of several significant categories of these instruments. On the asset side of the balance sheet, we must estimate the present value of held-for-investment (HFI) residential real estate loans and all other HFI loans. On the liability side, we must estimate values for three categories: subordinated debt, other borrowed money, and time deposits. Implicit in our approach is that these portfolios are replaced at the corresponding discount rate upon maturity.[15]

Ideally, we would have granular information on the remaining maturity, origination date,

[15] This is consistent with the typical pricing behavior of time deposits. 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 IA13b. It also reflects their use as a marginal form of financing in rate tightening cycles (Kang-Landsberg et al., 2023).

coupon, and risk characteristics of the positions we are valuing, but this information is not available for most commercial banks.[16] The Call Report does contain maturity schedules 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. Using the maturity data, our method calculating changes in the present value of these portfolios using estimated durations and changes in discount rates. We outline the logic of our approach below.

Based on the maturity schedules for each portfolio, we evenly assign book values to quarterly 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.

We derive the present value of positions in each time-to-maturity bucket, m, at time t, 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 at time t, 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, 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.[17] 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 reflects 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. To select these initial quarters, $t = 0$, we identified dates that reflect inflection points in the interest rate cycle when rates begin to rise relative to the recent past and we expect fair values and book values to be similar. The turning point

[16]The FR Y-14 reports contain detailed information on individual loans, securities, and debt instruments that could be used to generate instrument-specific valuations, but these reports are filed only by the largest bank holding companies (those subject to stress testing) and are available only since the mid 2010s.

[17]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.

dates we identify are: 1997:Q1, 1999:Q2, 2004:Q2, 2013:Q2, and 2021:Q4. This approach is consistent with the notion that fixed-rate instruments tend to be refinanced when rates are relatively low and is supported by aggregate data on the evolution of fair values relative to book values.[18] It is also similar to the approach used in literature examining changes in securities and loan values in the period immediately before the banking industry turmoil in March 2023 (Jiang et al., 2024; Flannery and Sorescu, 2023).

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 versus the actual 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. Hence, loans that exceed their book value because they pay higher rates than current market rates tend to be prepaid, which limits valuation gains relative to book value. For residential mortgages, we estimate industry-level prepayment rates using the NY Fed/Equifax Consumer Credit Panel; for all other loans, we assume a low prepayment rate of 5% per annum when interest rates are more than 50bps above recent levels and a higher rate of up to 30% per annum when rates are 100bps below recent levels.[19] We assume no prepayment of liabilities, which is a conservative assumption as it reduces the value of liabilities and its unclear if a distressed bank would be able to prepay and refinance.

Duration (D_t^m): We cannot calculate the precise duration of a portfolio with fixed-rate instruments. For instance, as noted above, we do not observe coupon rates, origination dates, or the precise time-to-maturity. Nor do we have a measure of risk for loans, such as a credit rating or probability of default. Thus, we approximate the duration by making several simplifying assumptions.

[18] In Figure IA6b and Table IA7 we show that the aggregate fair value of loans and securities tend to equal their book values around these dates.

[19] 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.

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.[20] For loans, we develop a variation on Equation 3 that incorporates expected prepayment rates that lower contractual durations.

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 with respect to maturity and risk.

For loans, we construct a *heterogeneous* (bank-specific, time-varying) discount rate that combines a risk-free rate of the proper maturity and a risk premium that is independent of maturity and incorporates bank-specific portfolio risk.[21] For each maturity bucket, we use a risk-free rate consistent with the corresponding GSW yield. For the risk premium, we construct a range using corporate bond indices, where a bank's assigned premium is determined by the relative rate on the loan portfolio conditional on maturity.[22] Specifically, we calculate the average interest rate on each bank's loan portfolio in each quarter as the ratio of interest expense on loans to loans outstanding. We account for differences in average loan maturities across banks by regressing the loan interest rates on information about portfolio maturity. We then use the residuals from these regressions as our measure of bank loan portfolio risk under the assumption that higher interest rates reflect riskier loans.

For liabilities, we do not want risk premia to lower the value of liabilities and increase EC, so we use risk-free or near-risk-free rates. For subordinated debt, we use GSW 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 ensure bank funding costs do not benefit from the liquidity benefits that depress Treasuries (Fleckenstein and Longstaff, 2024).[23]

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

[21] There is evidence that there is a term structure to risk prices (van Binsbergen and Koijen, 2017), but we leave further refinements on this dimension to future work.

[22] 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 to improve accuracy.

[23] This is particularly important during extreme conditions in the market (e.g., COVID, GFC) when GSW

Credit losses: For loans, we reduce our estimated present value for each bank-quarter by the proportion of loans that have been reserved against. One concern is that our use of risk premia in the discount rate effectively double counts default risk. While we cannot rule this out, we view our approach as conservative from a solvency perspective. Loan loss reserves tend to lag expected defaults, only being recognized slowly in the face of deteriorating loan performance.[24] On average reserves to gross loans are less than 1% and more than 99% of observations have reserves less than 3%, however, at the extreme, the share can range as high as 35%.

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 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 single-B (dotted line); however, during the GFC this is due to higher credit spreads and the recent cycle to higher risk-free yields. In both episodes, loan portfolio present values reach 90 percent or lower 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 do to a key valuation assumption. We assume that book values and present values are similar around turning points. This implicitly assumes that at issuance the discount rate on loans is equal to the the coupon rate, such that the present value reflects the principal on the loan. However, if part of banks' value creation is that they can earn returns on loans that exceed other forms of credit, Schwert (2020), then we are undervaluing the lending franchise of the bank and their loan portfolio. We are comfortable with this approach given it is conservative and is likely to more closely reflect the financeable value of loans when investors are concerned about its survival. Moreover, we lack details distinct from the interest rate as to the riskiness of the loan. We will take this into account when we consider the operating costs of the bank which would typically reflect costly monitoring that would help a bank achieve higher loan values that are ruled out by our approach.

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yields are extremely low but do not represent a viable funding opportunity for banks.

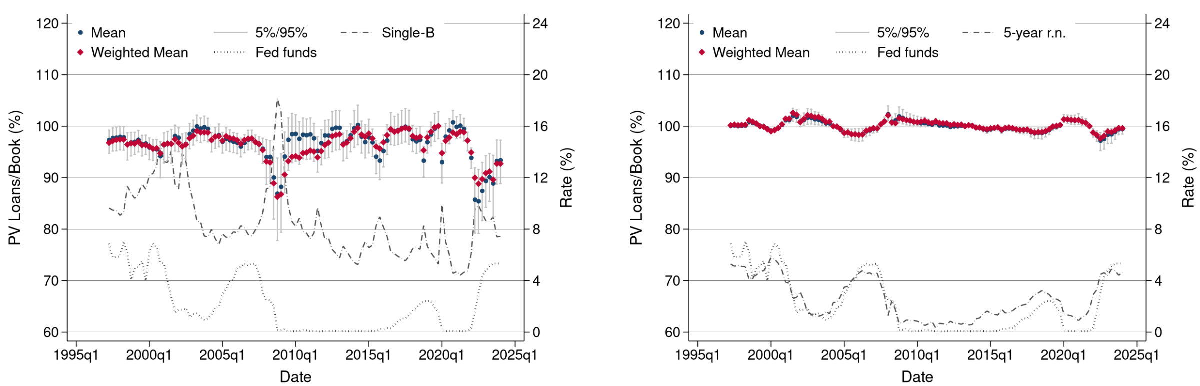
[24]Beginning in 2020, all U.S. banks were required to adopt a new standard, the Current Expected Credit Loss (CECL). CECL requires forward-looking recognition of credit losses over the entire life of the loan rather than the more backward-looking incurred loss approach that previously guided loan loss reserving. As a results, CECL-based reserves and provisions are likely to be more responsive to changes in economic and financial conditions and more likely to reflect differences in loan portfolio characteristics across banks.

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 shocks to credit spreads impair loan values but do not have a corresponding impact on fixed-rate liabilities. The treatment of liabilities as "risk-free" for discounting purposes also results in a much tighter distribution relative to loans as there is less heterogeneity. Discounting using near risk-free rates as well as the shorter maturity of liabilities results in smaller deviations from book value.

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 single-B yield and 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



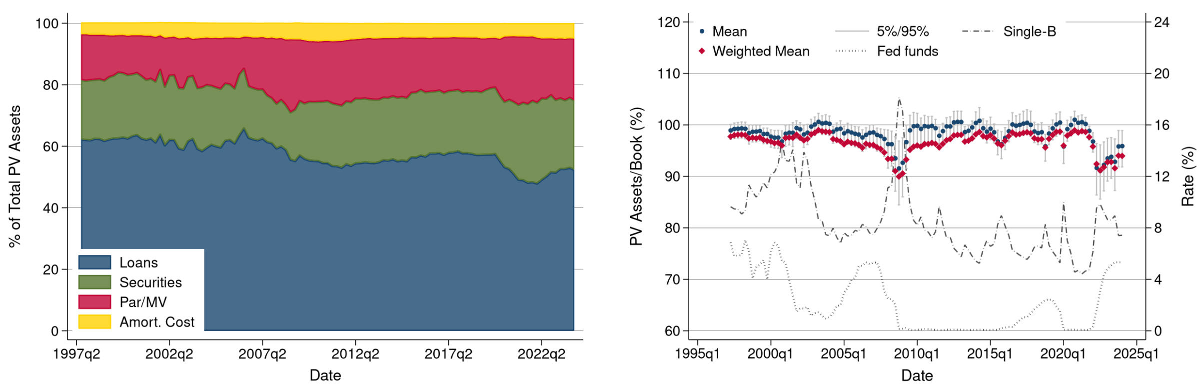
3.2.2 Estimated present value of assets

At this stage, we are able to calculate the total estimated value of assets over our sample period. We combine the loan portfolio valuations with appropriate valuations for other assets, including securities, cash, cash equivalents, and fixed assets. Figure 2a 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, though in present value terms, its share has decreased over time as the shares of securities and cash-like assets (e.g., reserves) have grown.

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 2b. 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

Figure 2. Asset values over time. These figures combine the estimated loan values with other assets values to summarize the total value of bank assets from 1997:Q2 to present. Figure 2a plots the composition of industry asset values. 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. Par/MV 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). Figure 2b plots the present value of assets relative to the book value of assets gross of reserves and includes the single-B yield and the fed funds rate. The chart includes the 5th-95th percentile range, the average and the weighted average.

(a) Industry Composition **(b)** PV Assets/Book



intangible assets in their book assets which we do not include in our estimates of present value (see Table 1). The next section estimates demand deposits and combines those estimates with fixed-rate liabilities to to obtain the total value of liabilities.

3.3 Demand deposits

Demandable debt introduces unique valuation challenges as the quantity and rate 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 multiple equilibria inherent in demandable debt by calculating a stress valuation using specific parameters.

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.[25] Hence, variation in implied demand deposit rates implicitly captures migration from NIB accounts

[25]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 IA13a.

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. Nevertheless, we use the same conceptual approach for each. We provide details and supporting evidence for our approach in IA Section C.1.

We calculate the present value of demand deposits as the function of financial terms: interest paid and effective maturity (i.e., drawdowns).[26] 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. Multiplying the valuation factor by the amount of deposits (e.g., the book value), $BV_{i,t}^{D}$, provides the present value.[27]

As Equation 4 makes clear, the present value of deposits increases with pricing and drawdowns (β and δ). As betas or drawdowns rise, a bank must fund itself at the discount rate rather than lower, quasi-fixed rates typically paid on demand deposits. In either case, the valuation factor approaches one (i.e., par value).[28] The present value of deposits decreases with the discount rate, y_t^D, holding beta and the drawdown rate fixed. As discussed further below, beta increases with the prevailing level of interest rates, so variations in rates have offsetting effects on the present value of demand deposits through their impacts on the discount rate and beta.

To facilitate valuing deposits in a standardized, parsimonious fashion across banks, we estimate bank-specific, time-varying betas conditional on a common drawdown rate. As a result, estimated betas will determine the cross-sectional differences in deposit value as well as changes in value over time. To estimate the key parameters, we develop an approach that links deposit pricing with financial conditions and deposit drawdown behavior. Deposits are subject to classic supply and demand dynamics — if banks set a higher relative deposit rate then deposit growth increases *ceteris paribus*. Indeed, when we estimate a reduced form

[26]As described in Section 3.4, we also account for the cost of providing banking services, which are critical to bank operations and servicing depositors.

[27]In practice, we incorporate the slope of the yield curve using a slightly more nuanced equation.

[28]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.

model of deposit pricing we find a robust positive relation between deposit prices and deposit growth.

Discount rates, y_t^D: Before estimating deposit terms, we choose a discount rate with which to model deposits. In the near-term, deposit rates are typically compared to other short-term rates, such as the fed funds rate. However, the present value is determined by expectations of future rates and future betas. 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., Office of the Comptroller of the Currency, 2024, Table 1d).[29] But these determinations lack clear empirical support. Absent distress, depository institutions typically retain pricing advantages to prevailing rates. In addition, microdata on the maturity of demand deposit accounts supports relatively long effective maturities (Sherman, 2013).

Based on these factors, we choose a universal drawdown rate of 5% per annum and calculate deposit values for each bank consistent with this rate. We also consider a stressed funding approach that effectively shortens the maturity of deposits. By considering a long-maturity scenario as well as a funding risk scenario, we are robust to this choice and able to capture the range of potential valuations.[30]

Deposit betas, $\beta_{i,t}$: Our approach to estimating deposit betas is designed to recover heterogeneity and time-variation in long-term betas conditional on deposit growth and interest rates. To do so, we estimate an empirical model that explains the long-term relation of deposit rates to interest rates as a function of bank and time factors. We then predict deposit betas for each bank-quarter conditional on interest rates and our chosen drawdown rate.

We focus on the terminal ratio of the deposit rate to the fed funds rate in five prior tightening cycles. We use the ratio of demand deposits to the fed funds rate at the end of a hiking cycle to capture long-term, cumulative sensitivities. Evidence shows deposit rates

[29] 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.

[30] We have also explored an even more extreme valuation approach that treats deposits as a perpetuity. Such an approach reduces the present value of low-beta demand deposits relative to other forms of financing and increases the level of EC, but does not change any of the core insights of the paper.

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 over a long horizon.[31] Moreover, sensitivities at low interest rate levels are less material to valuation compared to those at higher levels as the sensitivity of deposit value to beta converges to zero as interest rates approach the ZLB: $\partial DD/\partial\beta = y/(y+\delta)$.

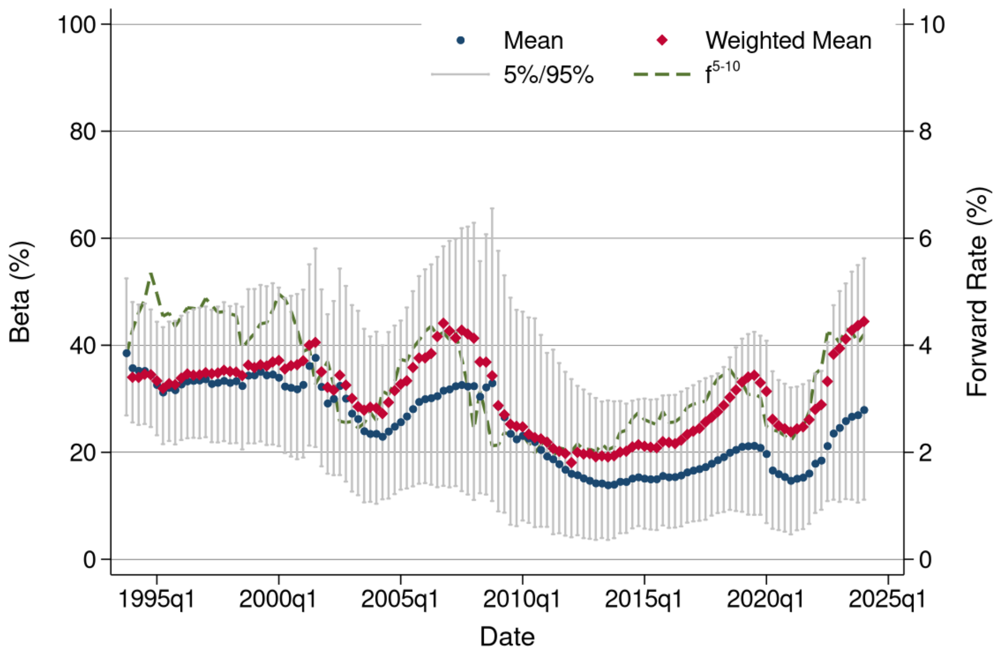
We regress bank-specific terminal betas for each hiking cycle in our historical sample period on an array of bank characteristics at the onset of rate tightening cycles as well the deposit growth per annum over the cycle. The bank characteristics highlight the nature of a bank's depositors, such as the average size of deposit accounts and features of the bank retail branch network. The model also includes cycle-specific variables such as the length of the tightening cycle and the 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 rates.

The resulting distribution of estimated long-term deposit betas across banks and over time is presented in Figure 3. The figure shows the range of estimated betas across banks 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 and the unweighted average across banks. Second, long-term betas are positively related to long-term rates. About 20 percent of the time-series variation in these betas is explained by changes in the long-term discount rate, with the remainder related to bank characteristics, such as the average size of deposit accounts and the role of retail branches.

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.

[31] The extant literature and supervisory practice have largely focused on using near-term relative changes to estimate deposit sensitivities. These are more relevant for capturing short-term shifts in earnings rather than long-term expectations of deposit rates. Near-term sensitivities can be quite different than those expected at longer horizons due 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)). We consider an alternative framework that estimates betas using cumulative changes in IA Section C.4 that yields similar estimates to our results, but has practical drawbacks for long-term valuation.

Figure 3. Estimated long-term betas. This figure plots the distribution of implied long-term demand deposit betas predicted by Table IA13, Column (1), conditional bank characteristics, a 5% drawdown rate, a cycle length of 12 quarters and the 5- to 10-year risk-neutral forward rate.



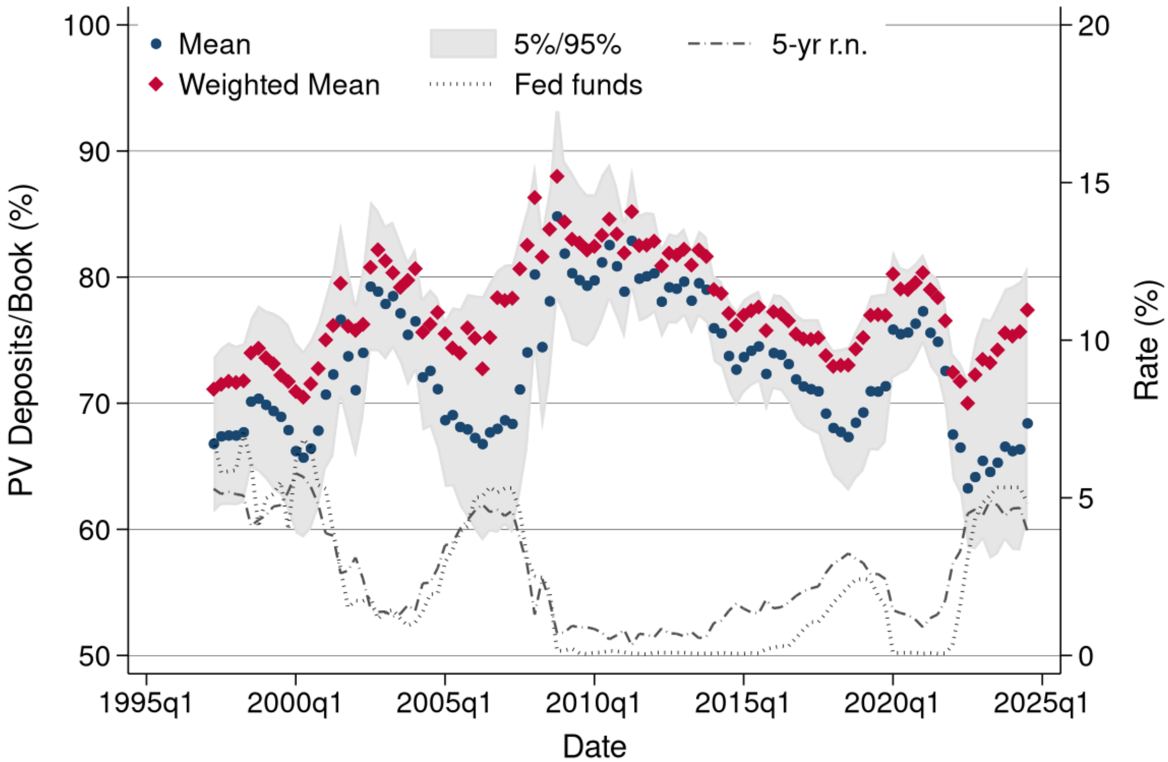
3.3.1 Estimated present values for demand deposits

Figure 4 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, with most values below 80 percent over the sample period. Demand deposit values are higher for large banks than for smaller banks, as weighted average values are larger than simple average values. The higher values reflect the higher estimated betas for large banks. Overall, demand deposit values are quite sensitive to the level of interest rates, especially compared to other bank liabilities (Figure 1b) with lower values and greater cross-bank dispersion when interest rates are high. This pattern suggests that the impact of higher discount rates dominates the impact of higher betas, as present values fall when rates rise, but that the large banks benefit less due to the greater sensitivity of their betas over time.

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 non-

Figure 4. 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 under normal business conditions. The chart includes the 5-year risk neutral yield and the fed funds rate.



interest 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 heterogeneous necessary expense levels 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 drawdown 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 rates 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 variable we estimate is the necessary expense ratio, $c_{i,t}$.

Necessary expenses, $c_{i,t}$: Similar to our estimates of beta, we develop an empirical model of bank expenses 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. 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 or maintaining loans that generate excess value. Hence, we assume (i) other noninterest income is zero (excluding deposit fees) and (ii) interest income and loan loss reserves are zero. 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.

3.4.1 Estimated present values of expenses

Figure 5b illustrates the distribution of necessary expenses and the present value of necessary expenses over time. Necessary expenses, Figure 5a, primarily range from 1-2% of assets. The results are consistent with economies of scale as the weighted average is roughly half that of the simple average. Expenses have trended down over time, particularly since the emergence of COVID in 2020:Q1, but grew slightly during the GFC. Relative to total non-interest expenses, Figure IA18, our estimate of necessary expenses in Figure 5a are lower, more stable and exhibit much less cross-sectional dispersion.

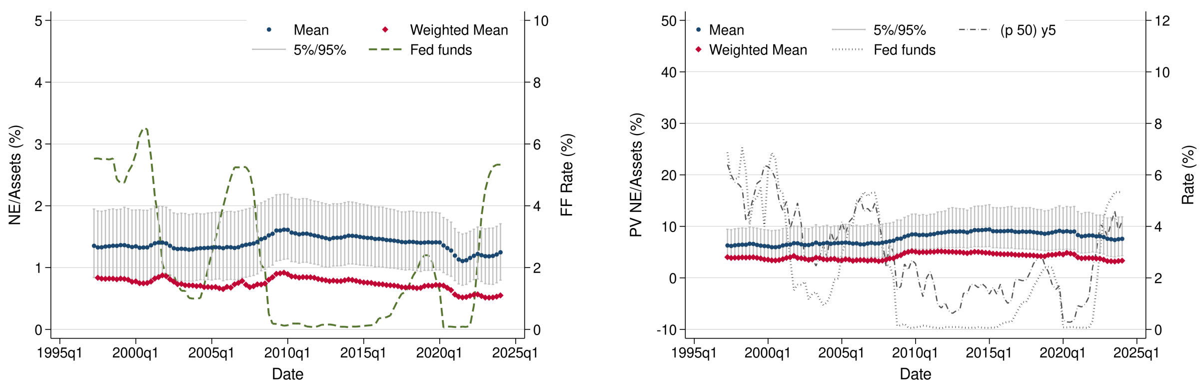
The simple average of the present value of expenses is higher than the weighted average, consistent with scale benefits. There is only modest time-variation, particularly for the largest banks.

3.4.2 Estimated present values for liabilities

Pulling all the liability side pieces together, Figure 6 shows the distribution of the present value of balance sheet liabilities and necessary expenses over time. Figure 6a contains the present value of liabilities scaled by total assets. On average, the value of liabilities equal just under 80 percent of assets prior to the Global Financial Crisis and has declined since that

Figure 5. Distribution of necessary expenses and present values over time. These figures plots the implied distribution of the necessary expenses and the present value of these expenses from 1997:Q2 to present. Figure 5a contains the distribution of necessary expense estimates relative to assets. Estimates are calculated using the coefficients in Table IA17 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 5b 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



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 3. Overall, however, the pattern of declining liability values relative to total assets holds for both larger and smaller banks.

Figure 6. Distribution of liability values. This figure plots the implied distribution of liabilities from 1997:Q2 to present. Figure 6a depicts the present value of liabilities to total assets. Figures 6b 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) PV Liab. | **(b)** PV Liab. + NE

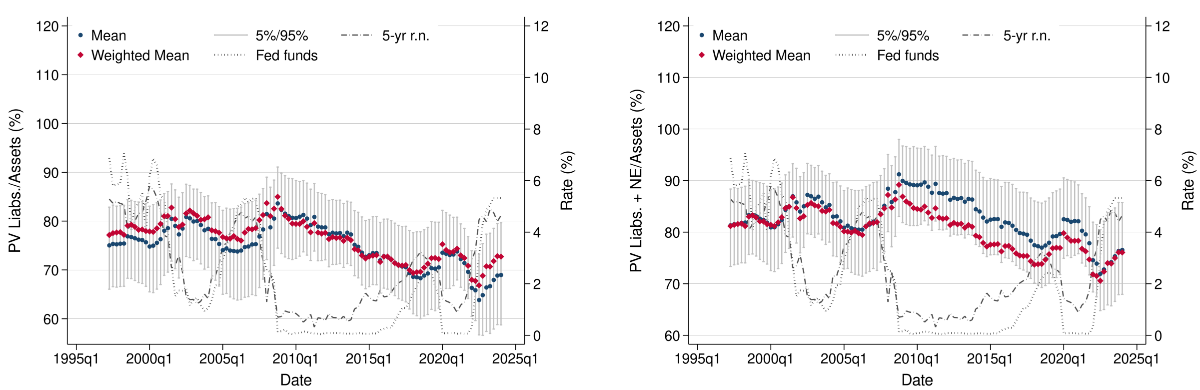


Figure 6b shows distribution of the combination of liabilities and necessary expenses over the sample period. The pattern over time is similar to that for liabilities alone, however the average bank now has higher liability values than the weighted average, particularly during periods of low rates, reflecting the higher level of necessary costs for smaller banks.

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.

3.5.1 Funding liquidity

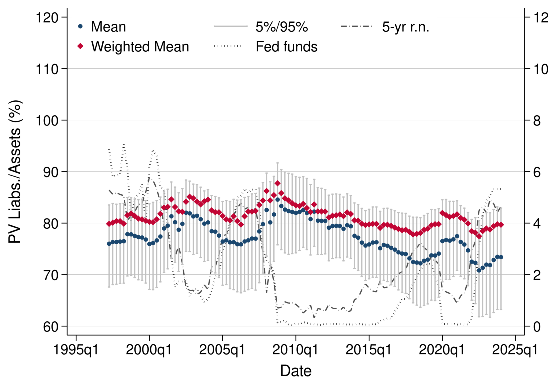
Funding liquidity, specifically deposit funding, impacts the value of bank liabilities. If deposit withdrawals will result in losses to creditors, then depositors may run to avoid incurring these losses. This logic has been applied most recently to assets that have been impaired due to interest rate movements (Drechsler et al., 2023; Haddad et al., 2023; Luck et al., 2023), but extends to a bank that is impaired due to any form of asset deterioration. If the solvency of the bank in a depositor withdrawal scenario is dubious, depositor behavior may change thereby lowering economic capital. This behavior is particularly important for uninsured or sophisticated depositors that are most responsive to information about bank solvency (Cipriani et al., 2024).

To assess the role of depositor behavior in economic capital, we consider two 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. The impact of this varies by banks and over time depending on valuation parameters and a bank's reliance on uninsured deposits. Banks that have sufficient asset value will be able to borrow at prevailing rates and still have ample economic capital, whereas banks that appear poorly capitalized in this scenario may not be able to borrow and may be economically insolvent.

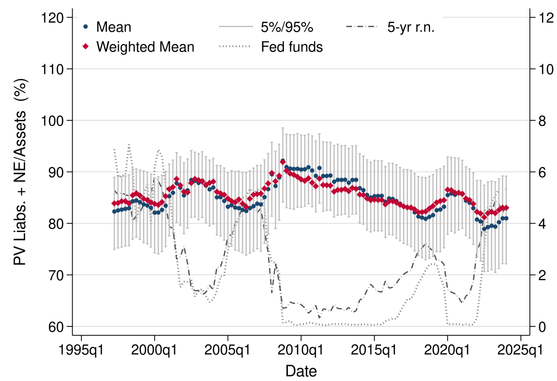
Figure 7 summarizes the impact of depositor behavior on the value of liabilities both with and without necessary expenses. The present value of liabilities is higher, reflecting the impact of higher deposit pricing. The difference from typical depositor behavior, Figure 6, is particularly strong for 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 7b.

Figure 7. 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 7a depicts the present value of liabilities to total assets. Figures 7b 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



3.5.2 Market risk and stress scenarios

EC measures are readily sensitized to a variety of 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 that the corresponding value also increases. Negative betas imply that an increase in rates lowers value.

With respect to interest rates, we multiply net interest rate betas by a 250bps instantaneous level shock to the yield curve which is roughly two times the annual standard deviation for changes in the five- or ten-year yield. With respect to credit risk, we multiply credit spread betas by credit shock associated with the bank's loan portfolio. The credit shock ranges from 250 basis point increase to the single-A yield to a 500bps increase to the single-B yield, which is again approximately equivalent to two standard deviations in the annual change. We discuss the results of these shocks in the next section.

4 Estimates of Economic Capital

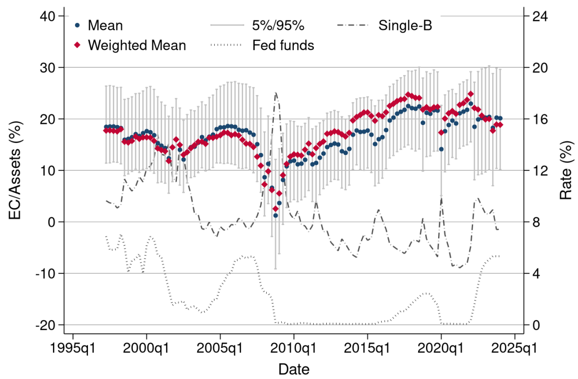
We combine the estimates of the present values of assets, liabilities, and necessary expenses to generate estimates of economic capital, Figure 8. For comparability with other solvency measures, we scale our estimates by reported book values of assets.

Figure 8a presents our estimates under normal conditions and Figure 8b under our depositor run scenario. Following a period of relative stability, EC ratios dropped sharply during the GFC, reflecting the impact of the substantial credit losses and sharply higher credit spreads during this period. Since the GFC, EC ratios have trended up. For most of the historical sample period, there are few systematic differences in EC ratios by bank size – simple and weighted average values are roughly the same – though EC ratios are higher for larger banks in the period following the GFC, when large banks in particular increased book equity in response to regulatory requirements.

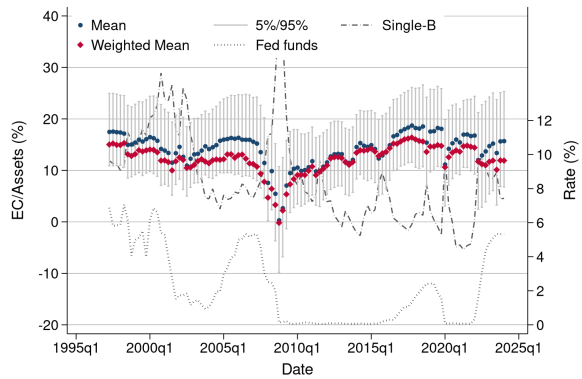
The apparent improvement in solvency assumes that depositors and market risks have remained stable. Under a scenario in which uninsured depositors react to bank capital, the benefits of greater EC are less clear. Figure 8b shows the distribution of economic capital

Figure 8. Distribution of economic capital over time. This figure plots the implied distribution of EC from 1997:Q2 to present. Each chart includes the 5th-95th percentile, the average and the weighted average. Figure 8a depicts the distribution of EC-to-assets; Figure 8b the distribution of R-EC-to-assets where uninsured deposits are assigned a beta of one. Each chart includes the single-B yield and the fed funds rate.

(a) EC



(b) R-EC



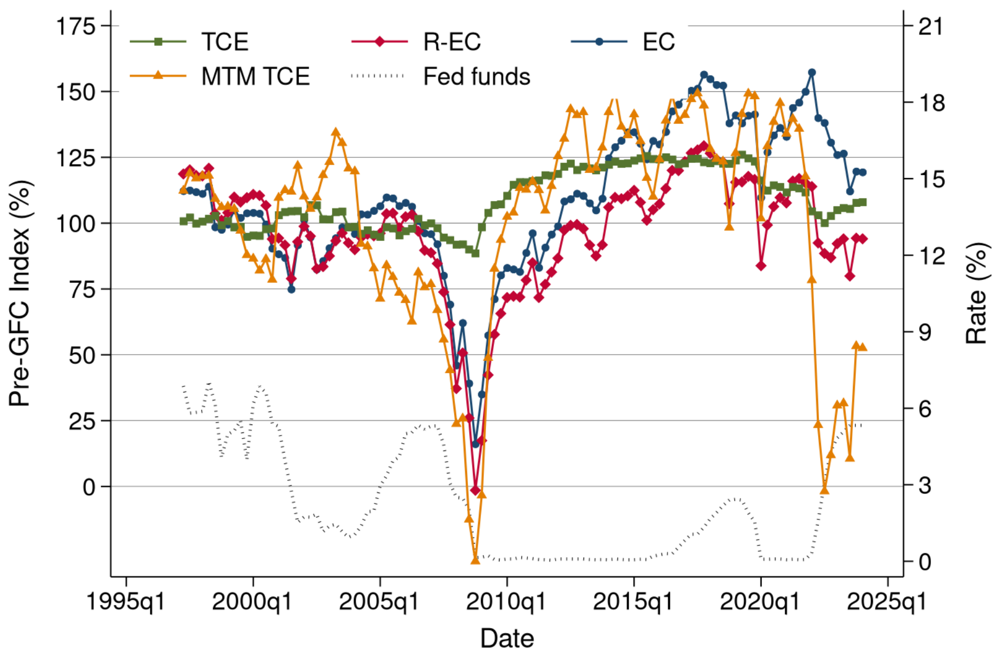
ratios when uninsured depositors are replaced with funding at market rates. Aside from the GFC — when R-EC ratios dropped sharply — the level of R-EC ratios has not changed meaningfully over time. If anything, R-EC ratios in the most recent period are below levels that prevailed prior to the GFC, especially for larger banks. After accounting for deposit 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 role of uninsured deposits.

4.1 Comparison to capital ratios

We can compare the evolution of EC and R-EC to TCE-based metrics of capital, Figure 9, to illustrate how EC measures vary over time relative to traditional metrics. As noted in Section 2, 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. We adjust TCE using the difference between the present and book value of assets to generate a marked-to-market TCE ratio (MTM TCE). For comparison purposes, we index all measures to equal 100 at their pre-GFC average values.

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. MTM TCE also rebounds quickly and is up to 50 percent higher in advance of COVID and the 2023 tightening cycle before plunging to levels that are consistent with the GFC. 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 metrics suggested for the period from 2010 to 2015. For the vast majority of post-GFC quarters, R-EC suggests the least improvement in banking industry capital buffers.

Figure 9. Industry capital ratios over time. This figure plots the evolution of industry capital ratios over time. For comparison purposes, we index ratios to their pre-GFC average (1997:Q2-2007:Q1).



4.2 Risk exposures

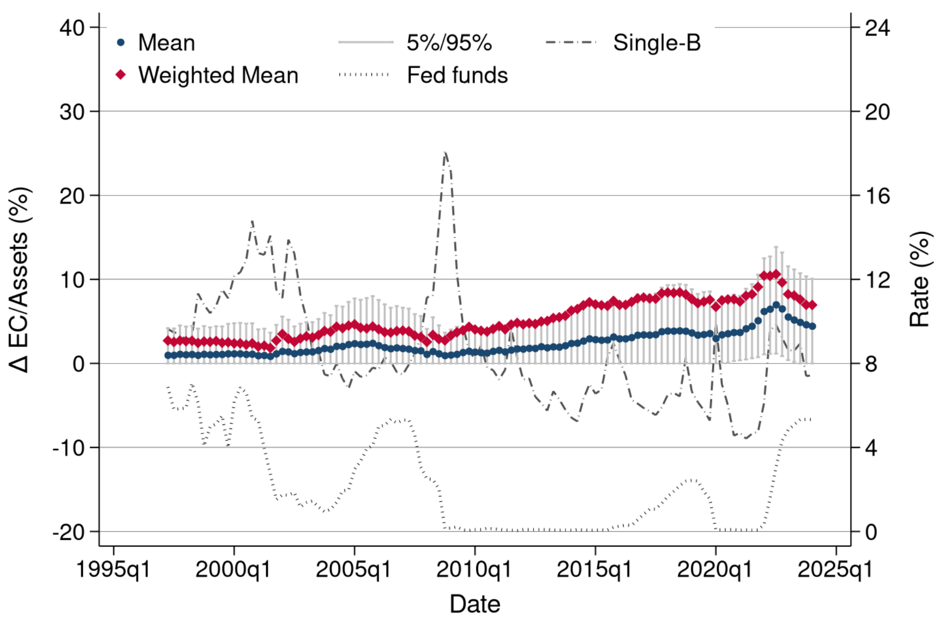
We can calculate the difference between EC and R-EC to obtain exposure to uninsured deposits. In this way, we can also use estimates of credit spread and interest rate betas, Equation 6, to obtain the exposure of banks to interest rates or credit spreads.

Figure 10 depicts differences in distributions over the historical sample period. As noted above, the gap between EC and R-EC has increased since the GFC, Figure 10a, reflecting the growing reliance on uninsured deposits, particularly for the largest banks. The rising levels imply the banking industry has become increasingly exposed to depositor behavior, especially in the period prior to the 2022 hiking cycle.

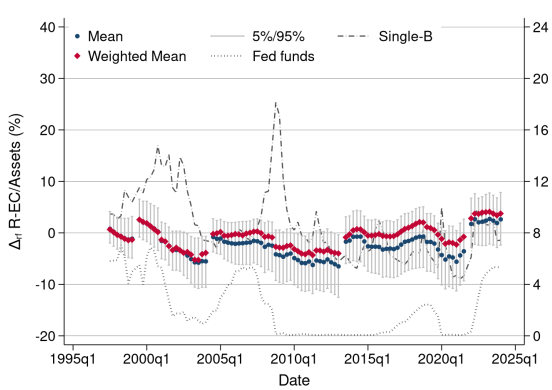
The growth of this exposure emphasizes the importance of investments in data collection and monitoring to better distinguish the risk of deposits across banks and over time. More detailed data on depositor characteristics (e.g., retail customers, corporate customers, non-bank financial institutions) as well as deposit terms would facilitate enhancements in deposit valuation modeling. An absence of regulatory metrics that incorporate deposit heterogeneity may incentivize banks to choose price- and risk-sensitive deposits over more stable forms of financing.

Figure 10. Distribution of risk exposures over time. These figures plot the difference between various EC measures to demonstrate the evolution of risk exposures in the banking industry from 1997:Q2 to present. Figure 10a depicts the difference between EC and R-EC; Figure 10b the difference between R-EC and R-EC when the yield curve increases by 250bps; and, Figure 10c the difference between R-EC and R-EC where the risk spreads increases by 250-500bps. 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.

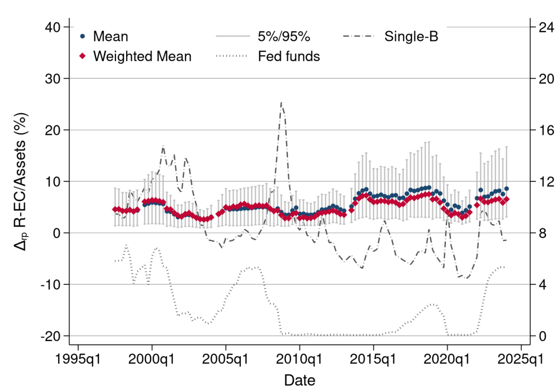
(a) Uninsured deposits



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



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



Figures 10b and 10c illustrate the evolution of the banking industry's exposure to interest rate risk and credit risk, respectively. Figure 10b shows the difference between R-EC and R-EC under a 250 bp interest rate shock and 10c shows the difference between R-EC and R-EC assuming increases in risk spreads. Positive values of these differences indicate that economic capital would decline under the interest rate or credit spread shock and thus indicate industry exposure to these risks.

Exposure to interest rates, Figure 10b, generally range around zero, consistent with the sensitivity of both assets and liabilities to interest rates (Flannery and James, 1984; Drechsler et al., 2021). However, the distribution suggests that there is significant variation in the cross-section whereby some banks face more or less exposure to rates. During the 2022 hiking cycle, exposure to risk free rates was elevated relative to the past thirty years, again, suggesting that the level of capital buffers was not as high as it would have appeared using unstressed (EC) or conventional (TCE) capital measures.

In contrast to interest rates, credit spreads only impact assets. Hence, a shock to credit spreads always poses a risk to capital. Exposure to credit spreads are heightened 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, unstressed measures of bank capital.

4.3 Bank Solvency

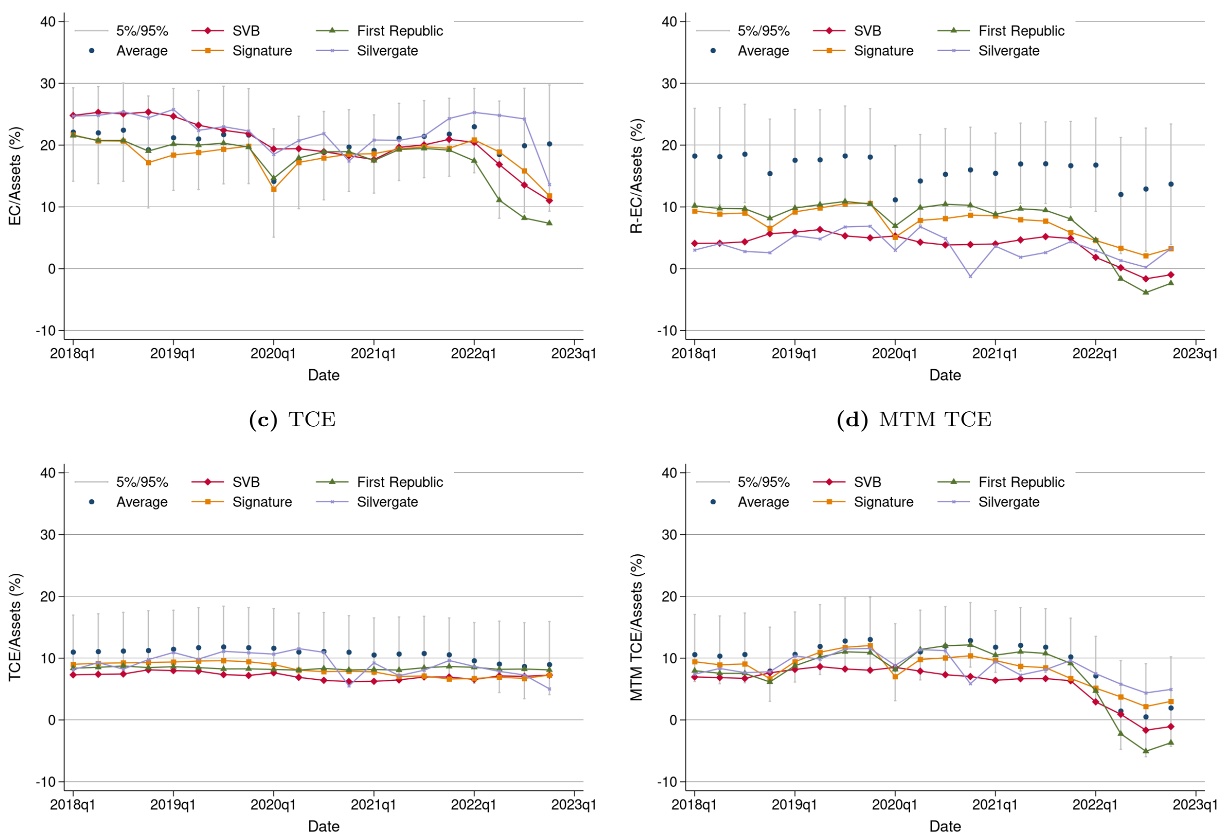
Thus far, we have focused on describing our estimates of economic capital and the financial stability implications. We now turn to results for individual banks to validate the information content of economic capital as a robust tool to assess bank health. First, we consider the recent episode of banking industry instability, March 2023, when sharp increases in interest rates decreased the value of bank assets leading to deposit runs at some banks. Then, we more broadly consider bank failure throughout the sample period from 1997 to 2023. This longer horizon is dominated by the 2007 to 2009 Global Financial Crisis (GFC), which involved large and unanticipated credit losses and severe declines in the value of risky securities. The two analyses provide distinct tests of whether economic capital is able to identify troubled banks in response to a variety of potential shocks.

4.3.1 Interest rate risk: March 2023

We focus our analysis on the four large banks that failed during the distress events in early 2023 – Silicon Valley Bank (SVB), First Republic Bank, Signature Bank, and Silvergate Bank. The key question is whether economic capital identified these failing banks as being at extreme risk in a more timely (i.e., sooner) or distinct (i.e., as more significant outliers) way than other solvency measures.

Figure 11 presents results for EC and R-EC along with TCE and MTM TCE. All measures are scaled by book assets. Each panel of the figure presents results for one of these measures for the four failing banks as well as the 5th/95th percentile range for all banks.

Figure 11. 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 11a depicts the economic capital-to-assets (EC); Figure 11b the run economic capital-to-assets (R-EC) where uninsured demand deposits are assigned a beta of one; Figure 11c the TCE-to-assets (TCE) and Figure 11d the MTM TCE-to-assets (MTM TCE).



(a) EC

(b) R-EC

(c) TCE

(d) MTM TCE

Figures 11a and 11b show the path of EC and R-EC, respectively, from 2018 to 2022:Q4, right before the onset of the banking industry instability 2023:Q1. As show in Figure 11a, the EC of the failed banks is quite sensitive to the rise in rates in 2022, with EC for these banks falling from about the industry average to around the 5th percentile. While their EC ratios are low, the failed banks are not stark outliers with respect to the overall distribution of banks: all four banks have EC ratios that are positive and that exceed the 5th percentile of the distribution at the end of 2022.

However, once we account for the repricing risk in uninsured deposits in R-EC, Figure 11b, we find that the four banks that fail have low economic capital in both relative and absolute terms well before they came under funding stress. First Republic and SVB have R-EC ratios that are near or below zero by mid-2022. Further, all the failing banks have R-EC ratios at or below the 5th percentile at the beginning of 2022, a year or more before they failed. Moreover, the R-EC ratios for SVB and Silvergate were outliers relative to the industry well before the start of the 2022 rate cycle – R-EC ratios for these banks were below the 5th percentile as far back as 2018. Thus, R-EC identified these banks' exposure to funding risk, relative to the rest of the banking industry, at least five years ahead of March 2023 episode.

Other measures of solvency, such as TCE or MTM TCE, where assets (but not liabilities) are marked-to-market, do not generate similar signals of distress for these firms. TCE ratios, Figure 11c, do not change meaningfully even as market values for assets deteriorate in 2022. The banks that fail have TCE ratios below the industry average but just above the 5th percentile over the course of 2022 – if anything, TCE ratios for SVB and Signature moved from the 5th percentile towards the industry average over this period (primarily due to a decline in the industry average). When we mark-to-market the assets using our present value of asset calculation, Figure 11d, the industry distribution of MTM TCE ratios falls in 2022, but the four failed banks do not appear to be outliers relative to the industry. All four have MTM TCE ratios above the 5th percentile and for Silvergate and Signature, above the industry average. The MTM plot 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 this point by considering the the four solvency ratios as of the 2022:Q3 before any clear signs of stress emerged. In the table, we focus on the 135 banks with assets greater than $10 billion, so that we have a sample that is roughly comparable in asset size to the four banks that failed. For each solvency measure, we rank the banks based on that measure from lowest (1) to highest (135) to assess the extent to which the failing banks appear as outliers relative to other large banks at that time. As shown in the first two columns, SVB and First Republic had the two lowest measures of R-EC, Silvergate was the sixth lowest, and Signature the 11th lowest. R-EC for First Republic and SVB were negative, another signal of weakness at this firm.

The third an fourth columns of Table 2 show the ranks under our EC measure that assumes deposit stability. The four failed banks rank relatively low, especially First Republic and SVB, but are not as extreme outliers as under the R-EC measure. Still, the EC values for First Republic, SVB, and Signature, which range between 8.19 and 15.9 percent, are meaningfully below the industry average of 21 percent.[32]

[32]The levels of R-EC and EC for the failed banks significantly lower than the average peer bank at 5% significance levels.

Table 2: 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 MTM TCE is the TCE less difference between book and mark-to-mariket assets where the MTM assets are based on our PV estimates.]

	R-EC		EC		TCE		MTM TCE	
	Rank	%	Rank	%	Rank	%	Rank	%
First Republic	1	-3.86	3	8.19	84	8.24	23	-5.06
Silicon Valley	2	-1.63	16	13.54	47	7.06	74	-1.65
Silvergate	6	0.23	100	24.24	56	7.28	123	4.38
Signature	11	2.11	29	15.85	41	6.72	112	2.18
Industry (> $10b)	69.92	10.37	68.95	20.62	68.34	7.67	67.54	-1.40

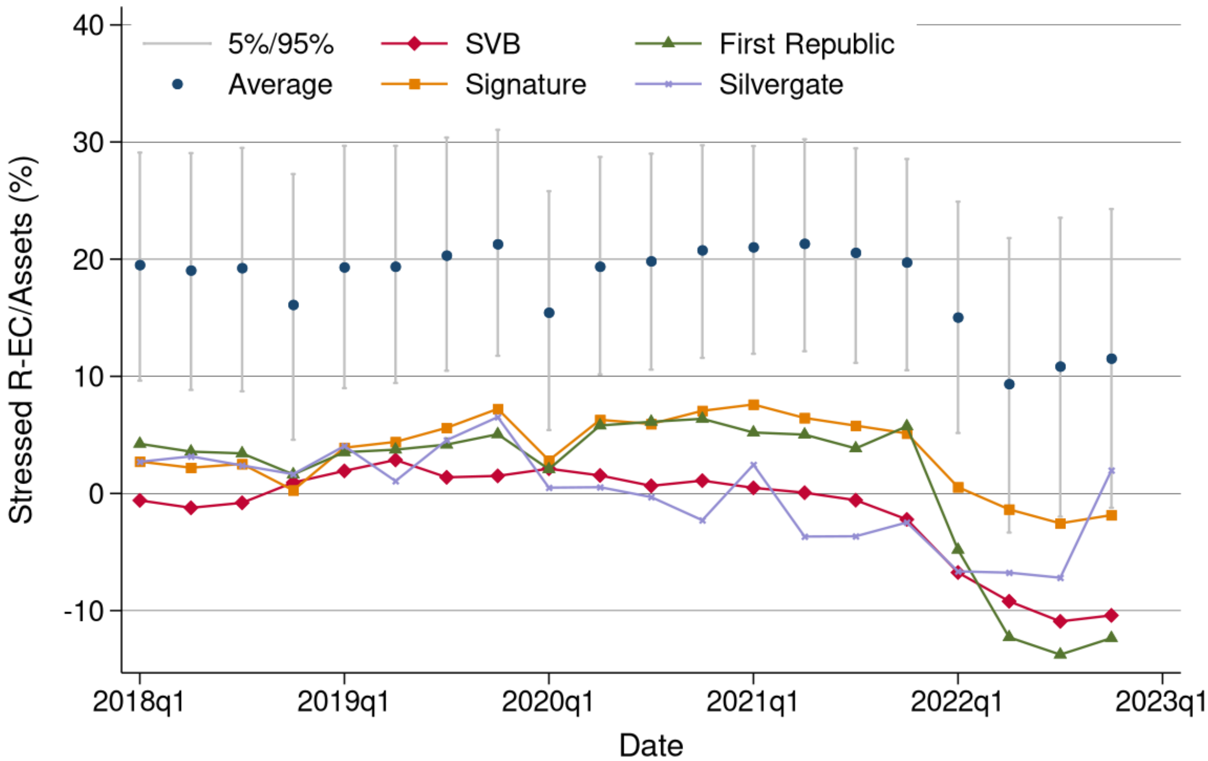
More conventional measures do not produce a signal of distress at the four failed banks. The final four columns show ranks under TCE and MTM TCE. The four failed banks do not stand out under these measures, even on the cusp of their failures. Under MTM TCE, SVB and First Republic have negative values, which theoretically signal distress. However, so many banks have negative values of MTM TCE that these banks are not particularly near the bottom of the distribution, ranking 74th and 23rd of 135, respectively. Silvergate and Signature, in contrast, have comparatively high MTM TCE measures, ranking near the top of the distribution.[33] Because it focuses only on one side of the balance sheet and due to the widespread nature of the asset value declines as interest rates rose, MTM TCE provided noisy and misleading signals of solvency risk right before the onset of the 2023 banking industry turmoil.

We further explore the ability of our economic capital measures to identify banks whose solvency is at risk by applying our +250bps interest rate scenario to R-EC to reveal banks most exposed to interest rate risk. Figure 12 presents the R-EC ratio incorporating this interest rate shift, highlighting the ratios for the four failing banks. The results emphasize the comparative weakness of the four failing banks, with all four having R-EC ratios below the 5th percentile from 2018 onwards.

Table 3 presents values of R-EC under the interest rate scenario ("Stress R-EC") for the four failed banks as of the end of 2021, a full two years before the banking industry stress and, more significantly, before the start of the interest rate cycle. The table also shows

[33] TCE and MTM TCE for the four failed banks are not statistically significantly lower than the average.

Figure 12. R-EC with interest rate stress: 2018:Q1 - 2022:Q4 This figure plots the run economic capital relative to assets assuming that risk-free yields at all horizons increase by 250bps in the quarter. 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.



contemporaneous values of our core EC and R-EC measures and a MTM TCE measure assuming the same 250 basis point increase in rates as in Stress R-EC ("Stress MTM TCE").

Both R-EC and stressed R-EC clearly identify the four failed banks as outliers with extreme solvency risk – Silvergate, SVB, Signature and First Republic have the lowest measures (ranks of 1, 2, 3, and 4, respectively, for Stress R-EC) among the 135 large banks. In contrast, Stress MTM TCE does not provide as clear a signal of solvency risk for all four banks. Stress MTM TCE values for Signature and First Republic are above average while Silvergate is above the 25th percentile. However, SVB does have negative Stress MTM TCE and is ranked fairly low in the distribution (11th).

Overall, the results in this episode emphasize that asset values and accounting-based capital do not distinguish failing banks from healthy banks. This is consistent with the joint assessment of asset risk and funding risk being critical to measuring the health of the bank.

Table 3: 2021:Q4: Stressed 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. Stress R-EC is the R-EC assuming a 200bps increase in risk-free rates. Stress MTM TCE is the MTM TCE where the MTM assets are based on our PV estimates assuming a 250bps increase in single-A spreads.

	R-EC		EC		Stress R-EC		Stress MTM TCE	
	Rank	%	Rank	%	Rank	%	Rank	%
Silvergate	1	4.39	76	24.31	1	-2.47	34	1.01
Silicon Valley	2	4.90	33	20.93	2	-2.21	11	-2.01
Signature	3	5.85	21	19.49	3	5.13	88	4.77
First Republic	5	8.05	20	19.19	4	5.73	81	4.23
Industry (> $10b)	69.99	14.70	68.93	23.28	70	16.33	68.44	3.37

4.4 Credit risk: Bank failures

The results in the previous section demonstrate that economic capital did a better job than more conventional TCE-based solvency measures at identifying the banks that failed during the 2023 banking industry stress. One concern with this finding could be that economic capital measures, especially those that embed stressed deposit funding assumptions like R-EC, might only be applicable to this particular episode of bank stress, where interest rate risk and deposit runs were prominent. Another concern is that EC measures are noisy indicators of bank health and therefore unreliable.

To test the ability of our EC measures to distinguish at-risk banks across a wider array of economic conditions we compare the ability of R-EC to predict bank failures relative to other capital metrics for the full sample period from 1997 through 2023. The resulting sample of 465 failed banks is dominated by failures during the GFC, as roughly two-thirds of failures occurred in the period from 2008 through 2010 when failures were primarily driven by housing-related credit losses. Credit losses represent the most common cause for banks failures, Correia et al. (2024), but as evidenced by the prior section are not the only source of bank distress — our objective is to develop a measure that is more comprehensive than current capital metrics,

First, we take descriptive approach to demonstrate where failing banks fall in the industry distribution for several capital metrics. We show that EC measures indicate these banks are weaker than their peers much earlier than typical measures. Moreover, EC measures suggest distressed banks that *do not* fail are in fact healthier than what conventional metrics would suggest. Then we statistically test the ability of our capital measure to distinguish between banks that fail versus banks that do not fail at various horizons and find that R-EC is a superior indicator of bank fragility. Overall, the results underscore that our approach to measuring solvency is more timely, comprehensive, and accurate than alternative capital measures.[34]

We identify bank failure events by merging the FDIC Failed Bank List with our data. We also identify a set of 'distressed' bank events defined using TCE.[35] To illustrate whether banks appear to be outliers relative to their peers in the run-up to failure/distress, we calculate the percentiles of capital measures in each quarter of the six-year period prior to the event. We then plot the average R-EC, EC, TCE and MTM TCE percentiles for banks that fail or experience distress in the preceding years. The idea is to see where banks are in the industry distribution of each solvency measure – the lower in the distribution, the more of an outlier the failing bank would appear to be.

Figure 13 summarizes the average percentile of banks around failure and distress events. For bank failures, Fig. 13a, the results suggest that both economic capital measures provided earlier and stronger signals of risk than the TCE-based measures. As early as six years (24 quarters) prior to failure, the average failed bank has an EC or R-EC in the lowest tercile of the industry. Further, the failed banks' average percentile begins to deteriorate more than five years prior to failure before accelerating around the two-year mark. In contrast to the 2023 period, when R-EC outperformed EC in identifying the banks that eventually failed, EC and R-EC provide essentially the same signal, on average, over the entire set of failed banks. This suggests that the heterogeneity in run risk may be more important for the recent episode than earlier episodes. The failing banks' TCE and MTM TCE percentiles are consistently in the middle tercile and stable/increasing until about 10 quarters prior to failure. As expected, in the final quarters prior to failure the metrics converge at or below their 5th percentiles.

If EC and R-EC do a better job of identifying failed banks than TCE-based measures, are they also less likely to incorrectly identify banks that do not fail (lower Type 2 error)? Figure 13b reports the average percentiles of the EC, R-EC, TCE, and MTM TCE measures

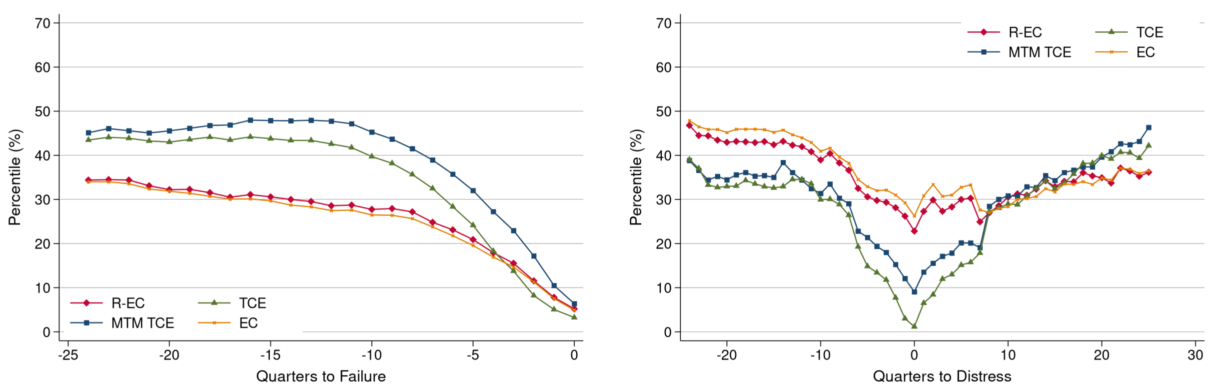
[34] We are not seeking to develop the best predictive model, but rather a more informative measure of solvency. Off-site supervisory models that are used to identify 'at-risk' banks (Cole and Gunther, 1998, e.g.,) and recent academic research (Correia et al., 2024) rely on multivariate models to optimize performance. Rather, we are highlighting that our single measure of bank capital is superior to comparable measures, indicating that it is a more forward looking index for evaluating solvency that can then be sensitized and easily interpreted.

[35] We define a bank-quarter as a distress quarter if it is the first quarter a bank has a TCE-to-Assets ratio below 3%. A plot of bank failures and bank distress events is available in Figure IA19.

for a set of banks that became distressed but did not fail. We define a distressed bank-quarter as the first quarter a bank has a TCE ratio less than 3 percent.[36] During the period from six years before to 10 quarters after the distress quarter, EC and R-EC percentiles exceed TCE and MTM TCE percentiles, consistent with the idea that the economic capital measures indicate lower solvency risk than the TCE-based measures. The gap between the economic capital and TCE-based measures widens sharply in the two years before quarter of peak distress, as the percentiles for TCE and MTM TCE fall sharply, while those for EC and R-EC decline considerably less. In sum, the economic capital measures indicate less financial stress than the TCE measures for these banks. One reason for this may be that EC measures suggest banks have more economic value which allows them to retain/raise funding to ensure their survival.

Figure 13. 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. 13a) and around periods of bank distress (Fig. 13b). 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)



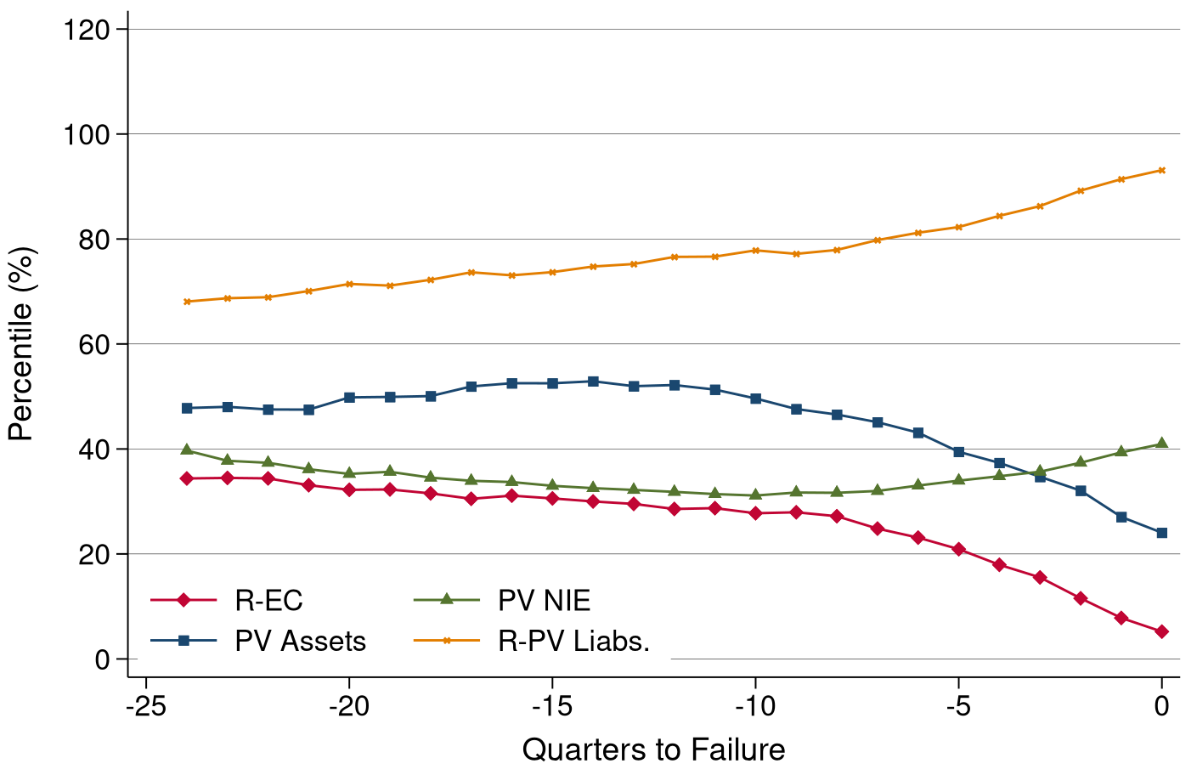
To understand what drives the superior performance of economic capital measures we decompose R-EC into its respective parts, Figure 14. The figure shows the average percentiles for the key components of R-EC — the present values of assets, liabilities, and non-interest expense. Each component is scaled by total assets plus loan loss reserves.[37] The figure

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

[37]We include loan loss reserves in the denominator so that the ratio can capture deterioration in credit quality 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

reveals that all three pieces contribute to R-EC, but that the present value of liabilities are a key piece to understanding why R-EC performs better than TCE measures. The present value of assets is similar to the industry for the three to six years prior to failure, only beginning to decline about three years out. However, the average percentile of the present value of liabilities is in the upper tercile six years prior to failure and rises over the entire pre-failure period peaking at around the 90th percentile by the quarter before failure. The average percentile for non-interest expense begins lower than the industry but rises in the 10 quarters before failure. Hence, the improved predictive power of economic capital measures appears to come from the inclusion of liabilities which provide important information about the cost of funding for banks that is otherwise excluded from TCE-based metrics.

Figure 14. 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.



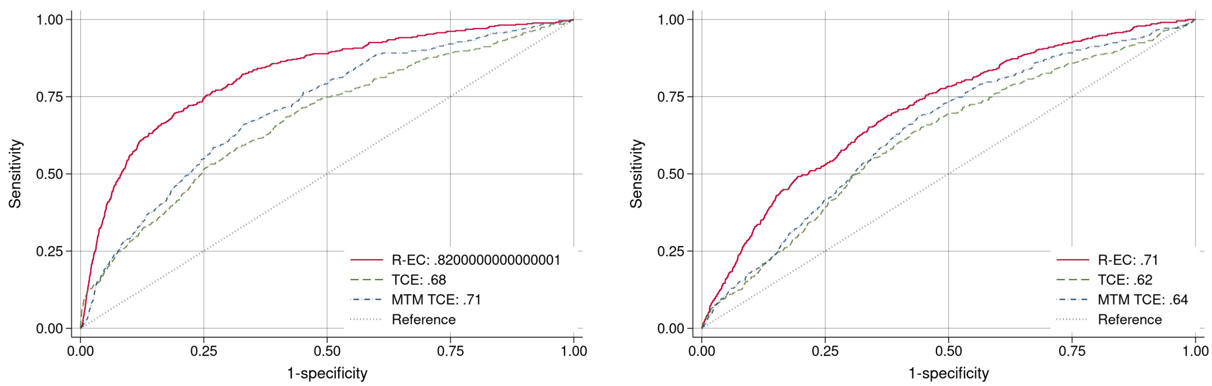
We formally test the predictive power of R-EC versus the TCE-based metrics using logit models. We estimate the ability of R-EC, TCE and MTM TCE to predict failure at 8 and 12 month horizons and then calculate Receiver Operating Curves (ROC). We then compare the

asstes plus reserves helps improve inference as to which fluctuations in value are potentially rising/falling in advance of failure.

Area Under the Curve (AUC) and plot ROCs 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 15. Receiver Operating Curves for solvency measures: 8- and 12-quarter lags This figure plots ROCs for a variety of measures of bank solvency. 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 models: one with an 8-quarter and a second with a 12 quarter lag. Line labels also report the AUC.

(a) 8-quarter **(b)** 12-quarter



At both the 8- and 12- quarter horizons, R-EC is more accurate than the alternative capital metrics, Figure 15. At the 8-quarter horizon, Figure 15a, the AUC is 0.82 versus the next closest metric, MTM TCE, at 0.71. The higher curve over the vast majority of specificity levels illustrates how much more accurate R-EC is for evaluating failure risk. At the 12-quarter horizon the results are similar but attenuated, Figure 15b, the AUC is 0.71 versus the next closest metric, MTM TCE, at 0.64. Hence, R-EC provides a better signal of bank health, as measured by potential failure, than accounting based alternatives.

5 Conclusion

We develop and implement a novel measure of bank solvency that incorporates the impact of changes in credit risk, interest rates, funding liquidity, and market risk over time. The measure is based on estimates of the present value of assets, liabilities, and necessary operational expenses, generating an internally consistent estimate of economic capital (EC). By stressing assumptions about depositor behavior – in particular, whether the bank needs to replace uninsured deposits with market-price funding – we can examine bank solvency under a variety of liquidity conditions. Our measure is based on publicly available regulatory report data for commercial banks, enabling us to calculate a comparatively long history that spans several interest rate cycles and episodes of banking industry stress.

Using economic capital, We are able to glean useful insights about vulnerabilities in the banking system and at individual banks. In particular, we find that banking sector capital has increased much more modestly since the GFC than what is suggested by alternative capital metrics, in part because the banking industry's reliance on the presumed stability of deposit funding has increased. We also show that system-wide exposure to interest rate risk peaked immediately prior to 2022 tightening cycle but remains elevated. Aside from highlighting these kinds of systemic exposures, our economic capital measure — particularly the measure that incorporates a funding run — identifies the large banks that failed during the 2023 banking stress well in advance and does a better job of identifying failing banks in general compared to more traditional, accounting-based measures of solvency such as TCE and market-adjusted TCE. Thus, our measures provide insights that are useful in evaluating and monitoring financial stability and for identifying potentially troubled banks across a range of economic conditions.

Because our measure is calculated using publicly available regulatory report data, it is transparent and can be replicated by others. That said, existing regulatory report data has a number of shortcomings, principally related to a lack of detail on the loan portfolio, the characteristics of deposits and depositors, and the composition of expenses. Better information in these areas would enable further refinements of our economic capital measures. In addition, the measures we have calculated do not incorporate the impact of off-balance sheet positions, such as derivatives and loan commitments, or activities taking place in non-commercial bank subsidiaries of consolidated bank holding companies. These are areas for further work. Future revisions of this paper will consider what minimum level of economic capital would reduce incidences of bank distress and how this might redistribute capital in the cross-section of banks.

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Internet Appendix for "Bank Economic Capital"

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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 zero-coupon 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
Single-B	ICE BofA Index (FRED)	BAMLH0A2HYB	$\geq$ 1997

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 broad maturity categories 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.

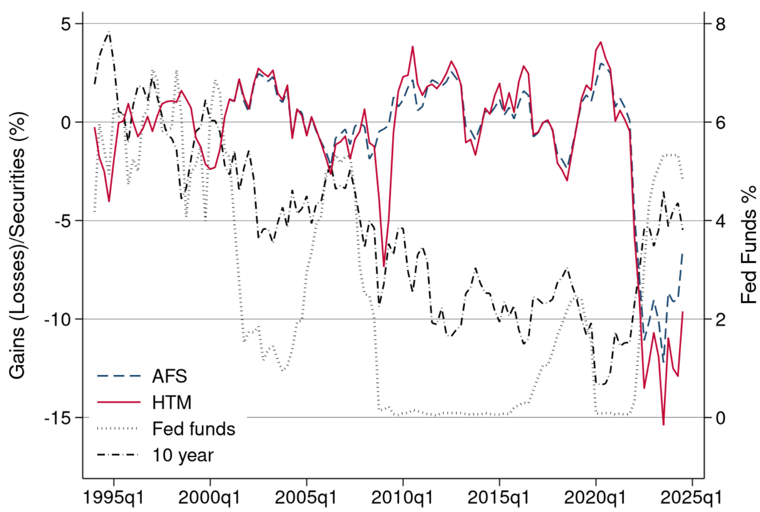
We ideally can identify the 1-4 family mortgage loans HFS and all other loans. There are two potential sources of information for the former that allow us to identify the mix of HFS loans. The first is in Call Report Schedule RC-P, line 4, which reports 1-4 family residential mortgages held for sale 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 $10m for two consecutive quarters. In addition, it includes loans held in the trading book ($<$ 3% of bank-quarters report trading assets greater than

[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. "

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. If a firm reports on 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 are smaller than the those of HTM portfolios, as evidenced by Figure IA5. 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 loans. This process is repeated for both loan categories. Table IA6 summarizes the process

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	-0.08	-3.15***	0.01	-4.16***
	(0.28)	(0.96)	(0.42)	(1.23)
Δ 10-year	-3.69***	-0.95	-4.04***	-0.27
	(0.51)	(1.02)	(0.54)	(1.36)
Lag HTM Gains/Sec.	0.95***		0.95***	
	(0.02)		(0.02)	
Lag AFS Gains/Sec.		0.00		0.00
		(0.00)		(0.00)
Constant	-0.31***	-0.95**	-0.32**	-1.28**
	(0.12)	(0.41)	(0.14)	(0.50)
Observations	440313	565776	156335	381934
Adj. ^{2}	0.95	0.09	0.95	0.13
Period	Full	Full	>2007:Q2	>2007:Q2
Y mean	-3.93	-1.14	-4.47	-1.54

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 Category	**Reported Value**	**Assigned: HFS FV**	**Assigned: 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	$A_1 = \min(M_1, A - \sum_j^5 A_j)$	$H_5 = M_5 - A_5$

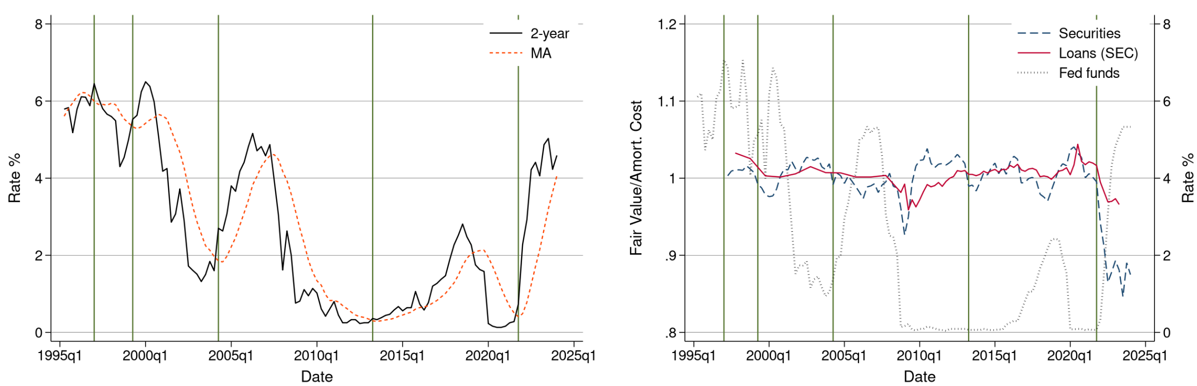
B.3 Initial values (PV_0)

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 illustrating the two-year GSW 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 (Call Report) and loans (sub sample of SEC filings) over time. Both are calculated as weighted averages.

(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 rate relative to the two-year moving average. We consider 1-year, 2-year, 3-year and 5-year risk-free rates. 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] For the 2- and 3-year maturity, we obtain the same dates, see Table IA7.[3] The table also illustrates the fair value-to-book value for securities (industry aggregates) and loans (sub-sample of fair values obtained from SEC filings) at these dates. 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 Equa-

[2]Similar cycle dates are obtained for most maturities even if we exclude the two quarter restriction.

[3]There are minor differences for the 5 and 1 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 (i.e., amortized cost). For these dates, we also report the fair value-to-book value for securities (industry aggregates) and loans (sub-sample of fair values obtained from SEC filings).

	FV/AC	
	Securities	Loans
1997q1	1.00	
1999q2	0.99	1.01
2004q2	0.99	1.01
2013q2	0.99	1.00
2021q4	1.00	1.02

tion 2 and the parameter values below. Banks that enter between cycle starts are assigned 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.

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 specific 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 the prepayment rate we reflect this in our present value calculation by assuming higher prepayment and no originations 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 2023. 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.[4]

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 various lags of long-maturity yields and the average mortgage spread relative to their moving averages. The coefficients on each term are negative and statistically significant which is consistent with falling rates increasing refinancing rates and rising rates reducing refinancings.[5]

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.[6] We use these time-varying estimates of δ in Equation 9 to calculate RRE durations for the range of maturity buckets over one year.

[4] Thanks to Donghoon Lee for providing these estimates. This is most likely a lower bound as prepayment will exceed refinance rates as home sales can also generate a prepayment event. With that said, home sales are a smaller fraction of prepayment events.

[5] The precise regression for quarter t is

$$\log(Rate_t) = -3.70 - 0.54Y^{30y}_{t-2} - 0.30Y^{5y}_{t-1} - 0.65Spread^{Mtg}_{t-2},$$

where Y^{30y} is the 30-year yield less its three-year moving average, Y^{5y} is the five-year yield less its three-year moving average, and $Spread^{Mtg}$ is the 30-year fixed rate mortgage spread (yield less the 10-year yield) less its three-year moving average. The R-squared from this regression is 70%.

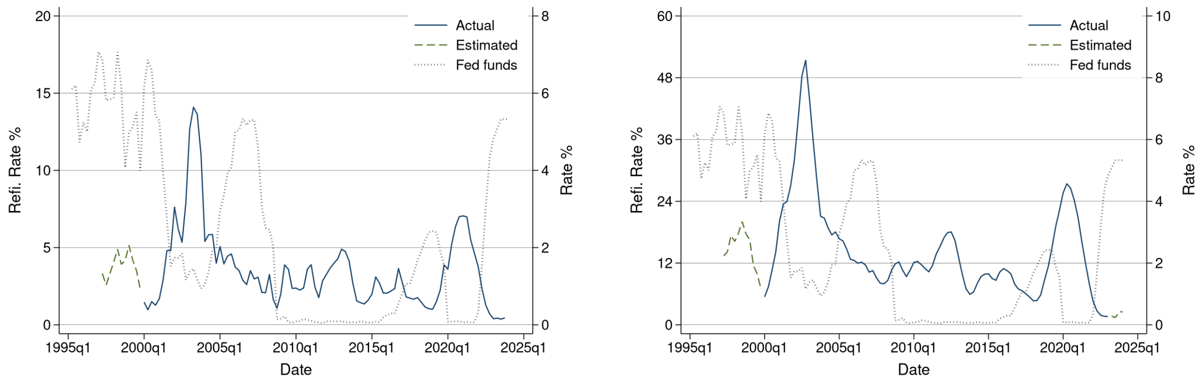
[6] We project 1-year forward refinance rates for the end of the sample period using the following regression,

$$\log\Big(Rate^{1y}_{t+1\to t+4}\Big) = -1.02 + 0.34\log(Rate_t) - 0.32Y^{30y}_t - 0.24Y^{5y}_t - 0.39Spread^{Mtg}_t.$$

The R-squared of this regression is 76% and the variable coefficients are all statistically significant at the 5% level. Y^{30y} is the 30-year yield less its three-year moving average, Y^{5y} is the five-year yield less its three-year moving average, and $Spread^{Mtg}$ is the 30-year fixed rate mortgage spread (yield less the 10-year yield) less its three-year moving average.

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 and 2024:Q3. Estimated rates are calculated using a linear regression of actual log refinance rates on several yields less their three-year moving average: the 30-year yield, the 5-year yield, and the mortgage origination spread. 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



For all other loans, we apply a simple rule that assumes a prepayment rate that ranges from 5% to 30% depending on the level of the BBB-yield relative to its recent history. If the two-quarter moving average (MA) exceeds the eight-quarter MA by more than 50bps, we assume prepayment is at its lower bound, 5%. If the two-quarter MA is more than 100bps lower than the eight-quarter MA, we assume that prepayment is 30%. Between these bounds we interpolate prepayment rates based on the the difference between the two moving averages. The sharp changes reflect the expectation that the mix of borrowers (e.g., CRE, C&I) will be more timely in their response to rate changes than RRE. 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

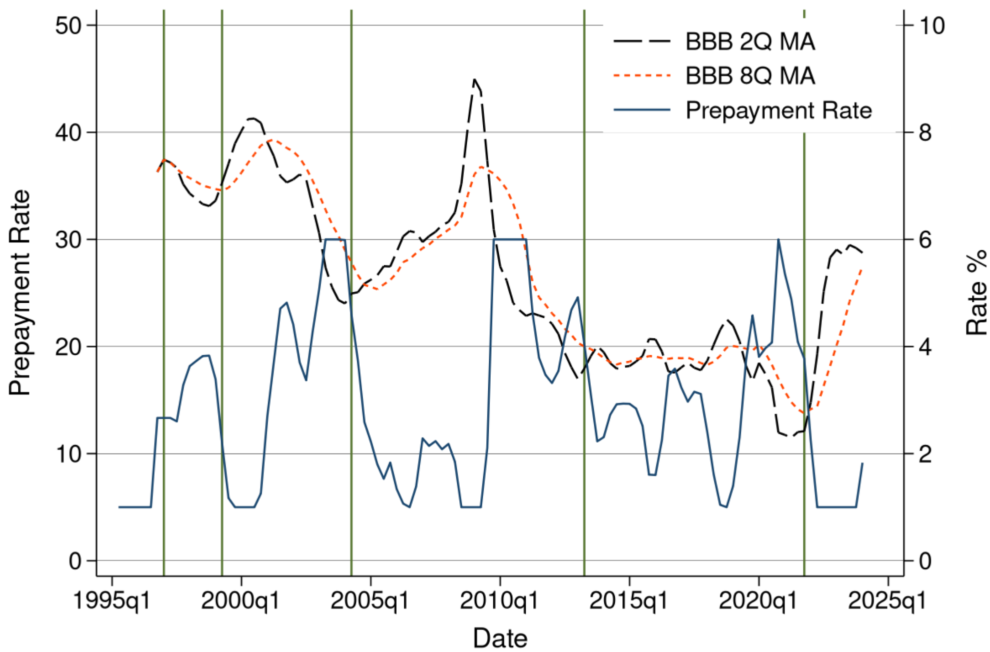
Risk-free rates, rf_t: For the risk-free component of discount rates, we estimate a rate for each quarter-to-maturity horizon m by interpolating rates using GSW yields.

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

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 GSW 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:

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

Figure IA8. All other prepayment periods. This figure plots the estimated prepayment rates for all other loans. Rates are bounded between 5% and 30% based on the level of the BBB-yield. If the two-quarter MA is greater than the eight-quarter MA by more than 50bps, prepayments are set at 5%. If the difference is less than -100bps the difference is set at 30%. 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. Then, we use these risk estimates to assign a risk premium that ranges from the corporate single-A spread to the corporate single-B spread. Our use of corporate spreads for all loans is based on data availability throughout our sample period. Conceptually, a similar exercise could be used for more granular loan types if corresponding indices were available.

To estimate the relative risk of bank loan portfolios, 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, $\overline{Loans_{i,t}}$,

$$r_{i,t}^{loan} = \frac{IntInc_{i,t}}{\overline{Loans_{i,t}}} \times 4 \tag{12}$$

We are able to do this separately for residential mortgages (RRE) and all other (AO) loans post 2007:Q4. However, interest income is not broken out between these two categories prior to 2008:Q1; therefore, we define loan rates for the total loan portfolio.

Loan rates have some negative realizations as well as extreme outcomes in the right tail, particularly if balances approach zero. We set negative realizations to zero and winsorize the right tail by quarter. AO loans and the total loan rate are right winsorized at 0.5%, RRE loans are more skewed so we right winsorize at 2.5%. Banks without a relevant loan balance are recorded as missing. See Table IA8 for a summary of loan rates and corporate spreads.

Table IA8: Loan rates. This table summarizes the benchmark yields and loan rates and credit spreads for banks in the sample. Loan rates are inferred for RRE (1-4 family first lien mortgages) and all other loans from 2008:Q1 onward.; total loan rates are presented for the period 1997:Q2 to 2007:Q4. The middle portion of the table presents loan rates winsorized by date at 0 on the left and 1% on the right. The final portion of the table summarizes the estimated spreads applied to discount rates. The single-A and BBB spreads reflect the lower bound spreads and the single-B the upper bound. Spreads are derived from the ICE US Corporate Bond Indices less the 5-year Treasury yield. Banks without a relevant balance are reported as missing.

	Mean	Median	SD	Min	Max	N
Loan rates (%):						
≥2008:Q1						
RRE loans	5.56	5.37	3.40	-933.33	400.00	357,609
Other loans	5.55	5.36	8.99	0.00	4,774.24	360,862
<2008:Q1						
Total loans	8.30	8.16	30.62	-131.70	16,324.32	309,806
Winsorized rates (%):						
≥2008:Q1						
RRE loans	5.51	5.37	1.44	0.00	14.85	357,609
Other loans	5.48	5.36	1.34	0.00	15.29	360,862
<2008:Q1						
Total loans	8.17	8.16	1.53	0.00	19.35	309,806
Spreads (%):						
≥2008:Q1						
Single-A	1.84	1.41	1.13	0.84	5.94	360,939
BBB	2.64	2.39	1.33	1.34	8.12	360,939
Single-B	5.95	5.27	2.65	3.22	16.59	360,939
RRE loans	4.03	3.51	2.25	0.84	16.59	357,119
Other loans	4.56	4.02	2.29	1.34	16.59	360,724
<2008:Q1						
BBB	1.96	1.83	0.70	0.93	4.09	309,781
Single-B	5.40	4.74	2.21	2.89	10.60	309,781
Total loans	3.62	3.17	1.69	0.93	10.60	309,781

The loan rates reflect the interest income relative to the book value of the loan portfolio, hence they are the yield on these loans at the time of origination. As a result, the risk premium does not correspond to prevailing market yields, but rather to yields at the time the loans were originated. While we do not know the time since origination, we do know the current maturity of the loan portfolio. To approximate the relative risk of each loan portfolio accounting for maturity, we regress implied loan rates on the maturity share of the loan portfolio for each quarter, t, and then calculate residuals which capture the interest earned on loans that is not readily explained by the maturity structure. Post 2007:Q4 the regression is done separately for RRE loans and all other loans.Prior to 2008:Q1 we regress the total loan rate on the comprehensive list of maturity shares.

Table IA9: Bounding loan discount rates. This table summarizes benchmark yields and average loan rates over time to assess the appropriateness of the benchmark yields as upper and lower bounds on loan risk. The single-A yield (lower bound) is compared to the average loan rate in the 10th percentile of relative risk. The single-B yield (upper bound) is compared to the average loan rate in the 90th percentile of relative risk. From 2008:Q1 onward, we apply the bounds to RRE (1-4 family first lien mortgages) and All Other loans separately. From 1997:Q2 to 2007:Q4, we apply the bounds to the entire loan portfolio. Bank-level loan rates are winsorized by date at 0 on the left and 1% on the right. Note that banks without a relevant balance are reported as missing.

	Mean	Median	SD	Min	Max	N
≥2008:Q1						
Lower bound:						
Single-A	3.66	3.11	1.46	1.52	8.23	65
RRE (p5)	3.40	3.34	0.31	2.92	4.21	65
BBB	4.44	4.06	1.51	2.06	9.67	65
All Other (p5)	4.44	4.37	0.56	2.95	5.60	65
Upper bound:						
Single-B	7.68	7.01	2.64	4.42	18.14	65
RRE (p90)	7.73	7.34	1.07	6.62	12.07	65
All Other (p90)	7.13	7.08	0.59	6.32	8.76	65
<2008:Q1						
Lower bound:						
BBB	6.48	6.50	1.03	4.59	8.43	43
Total (p5)	6.92	6.95	0.84	5.49	8.07	43
Upper bound:						
Single-B	9.90	9.45	2.25	6.80	14.79	43
Total (p95)	10.50	10.01	1.33	8.70	12.68	43

We use these residuals, denoted $\varepsilon_{i,t}$, as an estimate of relative risk for each loan portfolio at a point in time. We then map these residuals into a range of credit spreads which can be used to construct discount rates that are commensurate with risk. We set upper and lower bounds for the riskiness of loan portfolios using corporate credit spreads. The left tail of the distribution of relative risk, ε_t^{lb}, is assigned a single-A spread for RRE loans and BBB spread for AO loans and total loans (pre-2008). For the right tail, ε_t^{ub}, we use the single-B spread for all loan types. This process is repeated for each quarter. Based on the these bounds we assign bank loan portfolios to a continuum from the lower to the upper bound spread depending on their relative risk in the range between the left and and right percentile bounds,

$$\omega_{i,t} = \begin{cases} 0, & \text{if } \varepsilon_{i,t} \leq \varepsilon_t^{lb}, \\ \frac{\varepsilon_{i,t}-\varepsilon_t^{lb}}{\varepsilon_t^{ub}-\varepsilon_t^{lb}}, & \text{if } \varepsilon_t^{lb} < \varepsilon_{i,t} < \varepsilon_t^{ub}, \\ 1, & \text{if } \varepsilon_{i,t} \geq \varepsilon_t^{ub}. \end{cases} \tag{13}$$

For RRE and all other rates from 2008 onward, we use the 5th/90th percentiles of $\varepsilon_{i,t}$ to define the lower/upper bounds ($\varepsilon_t^{lb}/\varepsilon_t^{ub}$ in Equation 13); for total loan rates pre-2008 we use the 5th/95th percentiles. The choice of percentiles is based on the approximate correspondence of implied loan rates to the lower and upper bounds (see Figure IA9). To minimize non-fundamental volatility in risk premia, we take the 4-quarter moving average, $\overline{\omega_{i,t}}$, and then calculate the risk premium for each loan portfolio.

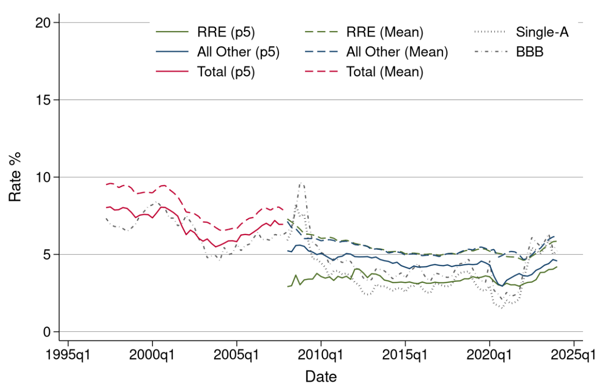
$$rp_{i,t} = (1 - \overline{\omega_{i,t}})Spread_t^{lb} + \overline{\omega_{i,t}}Spread_t^{ub} \tag{14}$$

The final result is a risk premium, $rp_{i,t}$, for each bank loan portfolio that ranges from the single-A or BBB credit spread (safest loans) to the single-B credit spread (riskiest loans).

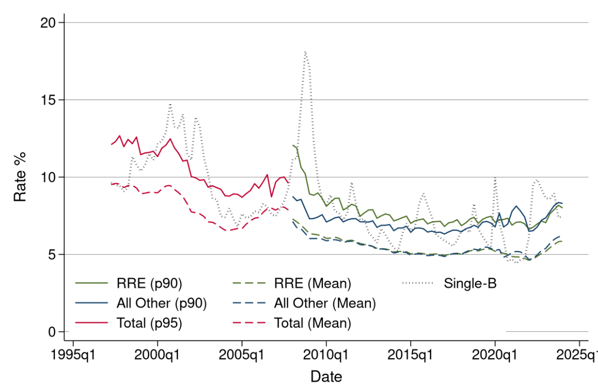
We chose the relative risk percentile bounds because so that they approximately correspond to the corresponding credit spreads. Table IA9 summarizes the average loan rates in the chosen percentile bounds as well as the single-A, BBB and single-B yields. As noted above, inferred loan rates are not mark-to-market yields but rather a weighted moving average of yields at origination; therefore, loan rates will be attenuated relative to market rates. In addition, loan portfolios may have a different maturity than the chosen credit index. Nevertheless, we would like the average rate for bounded portfolios, particularly in a stationary environment, to roughly align with the chosen credit spread. After 2007, the bottom 10th percentile of RRE and All Other loans are 3.4% and 4.4%, respectively, whereas the single-A average is 3.7% and the BBB is 4.4%. The top 90th percentile of rates are 7.7% (RRE) and 7.1% (AO) compared to the single-B average of 7.7%. Prior to 2008, we compare the BBB and single-B yields to total loan rates. The loan rate for banks in the lower 5th percentile of relative risk is 6.9% versus the BBB yield of 6.5% and the top 5th percentile has an average rate of 10.5% versus the single-B of 9.9%. Figure IA9 depicts these comparisons over time.

Figure IA9. Bounding loan discount rates. This figure plots loan rates for banks with low and high relative loan risk relative to the credit spreads we apply to those banks. We consider the total loan rate for the period prior to 2008:Q1 and RRE and AO loans separately for the period after 2008:Q1. Figure IA9a depicts the average loan rate for the banks' with low relative loan risk (the bottom 5th percentile of the relative risk distribution) as compared to the single-A and BBB corporate bond indices. Figure IA9b depicts the average loan rate for the banks' with high relative loan risk (the top 90th or 95th percentile of the relative risk distribution) as compared to the single-B corporate bond index. Note that the estimated loan rates are based on yields at origination, so the rates will not vary with short-term movements in market rates. The objective is to capture the average level of spreads over time.

(a) Lower Bound



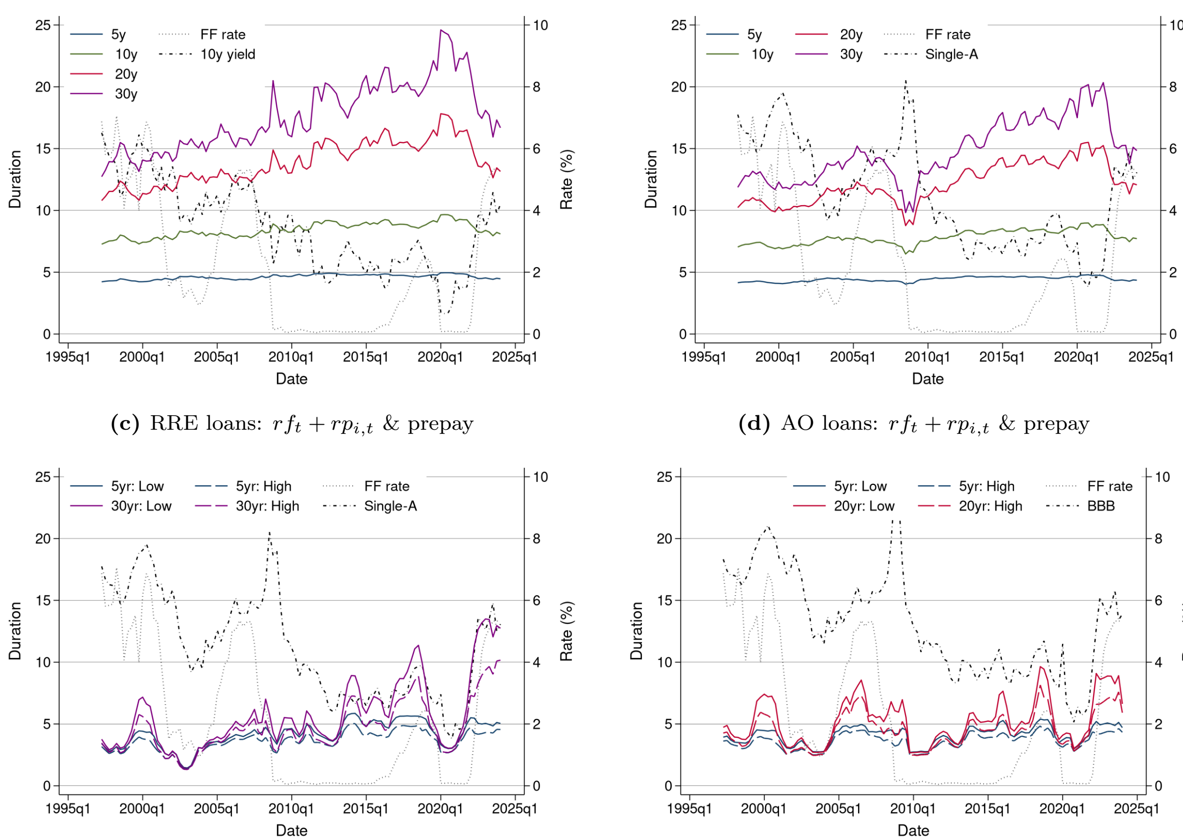
(b) Upper Bound



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 IA10 illustrates how risk premia and prepayment impact duration for asset portfolios (e.g., loans). The risk-free durations, Figure IA10a, 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 single-A risk premia, Figure **??**, 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 IA10c and IA10d, significantly reduces implied duration, especially during high prepayment periods.

Figure IA10. 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 IA10a depicts implied durations using GSW risk-free rates. Figure IA10b includes a risk premium for all banks in the form of the the Single-A spread. Figures IA10c and IA10d show the range of durations using our estimates of heterogeneous risk premia (Figure IA9) and prepayment for RRE and all other (AO) loans, respectively. The low risk durations (Single-A) are depicted in solid lines and the high risk durations (Single-B) are depicted in the dotted lines.



(a) Risk-free: rf_t

(b) Risk premium: $rf_t + rp_t$ (Single-A)

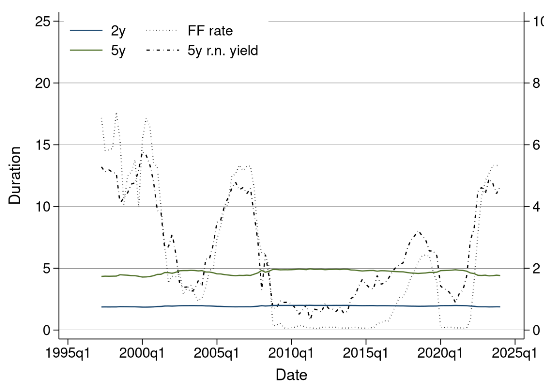
(c) RRE loans: $rf_t + rp_{i,t}$ & prepay

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

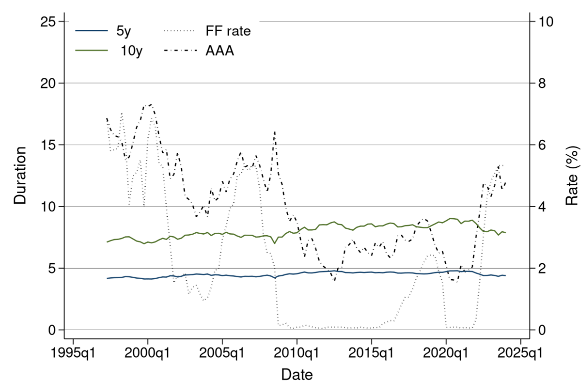
Figure IA11 illustrates how implied duration varies across liability time-to-maturity buckets. Liabilities use relatively risk-free rates and do not allow for prepayment. Liabilities also cover a a shorter range of maturities than assets. For time deposits and other borrowing we use risk neutral yields; the range of durations is depicted in Figure IA11a. For subordinated debt we use GSW yields plus the AAA credit spread implied by the ICE corporate bond index, Figure IA11b.

Figure IA11. 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 IA11a depicts implied durations using ACM risk-neutral rates. Figure IA11b 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)



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 to domestic and pricing behavior appears significantly 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 nontime deposits for each bank i and each quarter t divided by the average deposit balance between the current and prior quarter, $\overline{Deposits_{i,t}}$,

$$r^D_{i,t} = \frac{IntExp_{i,t}}{\overline{Deposits_{i,t}}} \times 4. \tag{15}$$

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 implied rates are summarized in Figure IA12.

Figure IA13a 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.

Time deposit behavior is distinct from demand deposits. While time deposit share is also cyclical, Figure IA13b 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.

Figure IA12. Implied 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).

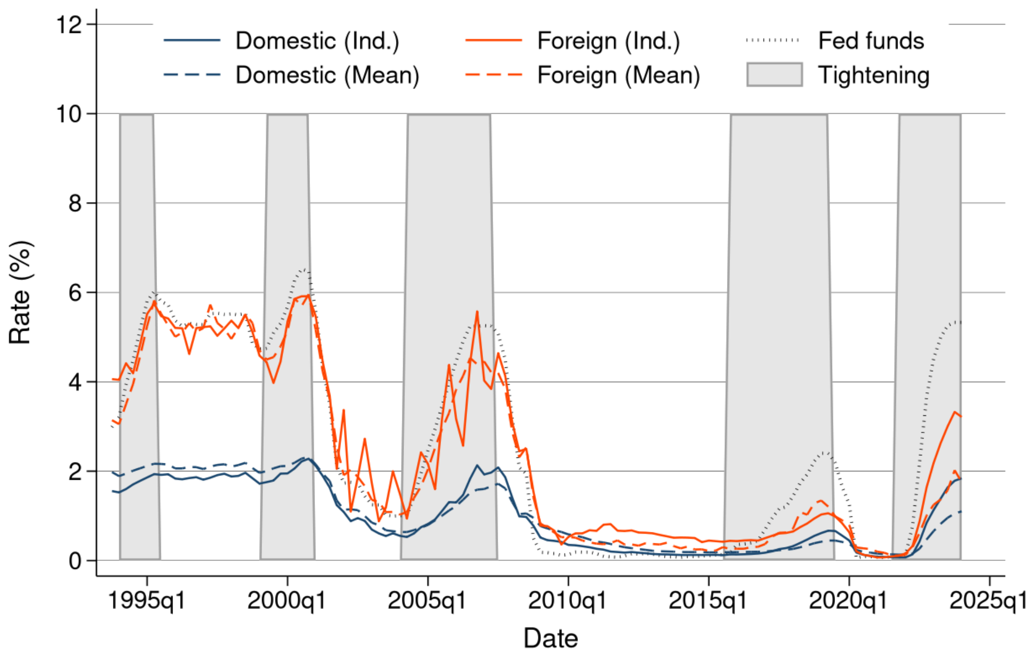
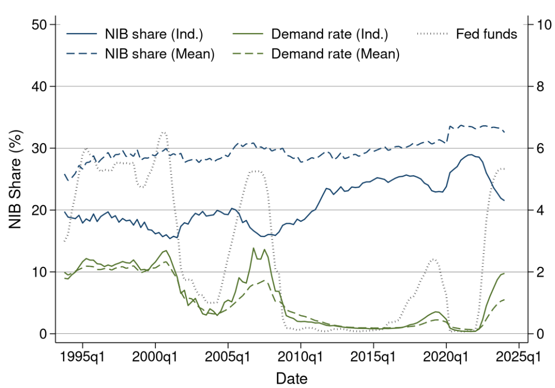
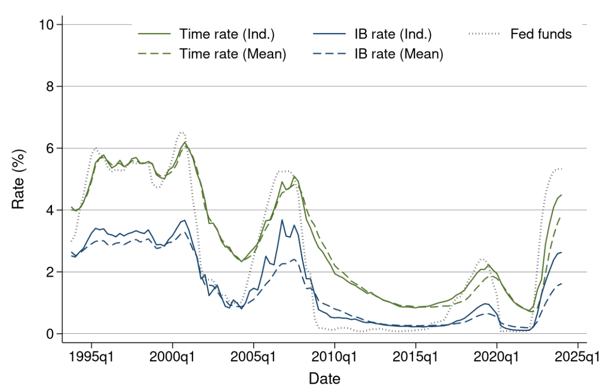


Figure IA13. Deposit composition and rates. These figures plot deposit composition and deposit rates over time. Figure IA13a plots the share of noninterest bearing deposits relative to demand deposits and the implied overall demand deposit rate. Figure IA13b plots the time deposit rates and IB rates. Both plots consider the industry (solid lines) and the average (dotted lines).

(a) Noninterest bearing



(b) Time deposits



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

$$DD_{i,t} = \sum_{k=1}^{5}(1-\delta)^{k-1}\frac{\beta_{i,t}^{k} f_t^k + \delta}{(1+y_t^k)^k} + \left(\frac{1-\delta}{1+y_t^5}\right)^5 \frac{\beta_{i,t} f_t^{5-10} + \delta}{f_t^{5-10} + \delta}, \tag{16}$$

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 estimated and near-term betas at each horizons, $\beta_{i,t}^k$ are equal to these estimates as long as the corresponding forward rate is greater than 25bps (otherwise the beta is set to 1). The PV-per-dollar, DD, is then multiplied by the book value of demand deposits to obtain the present value in dollars. The intuition from Equation 4 remains, but can generate modestly different estimates ($< 5\%$ at typical parameter values) when the yield curve has a significant slope. In a flat rate environment the results are identical.

C.3 Deposit sensitivities

As outlined in Section 3.3, our empirical approach is to recover long-term deposit betas that are most relevant to valuation. We define two measures of how deposit rates respond to interest rates over time: the relative level of deposit rates to interest rates and the relative change of deposit rates to interest rates. Given our findings, our primary focus will be on the former. For the final quarter of each interest rate cycle, T, the measures are:

$$B_{i,T}^R = \frac{r_{i,T}^d}{ff_T}$$
$$B_{i,T}^C = \frac{\Delta r_{i,T}^d}{\Delta ff_T},$$

where $r_{i,T}^d$ is the implied demand deposit rate, ff_T is the average daily fed funds rate in quarter T, and Δ denotes the change from the initial quarter of the interest rate cycle to T.

The long-term forward rates from Equation 16 are the relevant rates for thinking about long-term sensitivities. The beyond 5-year forward rates we construct from the ACM risk-neutral yields never fall below 1.9%, hence the relevant sample of ratios are those at the end of hiking cycles. We plot these two sensitivities relative to the Fed funds rate in Figure IA14. For the ratio of deposit rates to the fed funds rate, B^S, the level of the fed funds rate and short-term rate dynamics play an important role, but ratios revert to similar levels as cycles mature and the fed funds rate is at the more empirically relevant levels north of 2%. For the cumulative change, rates tend to rise over the cycle, consistent with deposit convexity. In both case, the figures illustrate the importance of thinking about long-term sensitivities at elevated rates as distinct from short-term sensitivities which reflect transient conditions that are not reflected at long horizons.

Figure IA14. Tightening cycles and deposit sensitivities. These figures plot deposit rates and two measures of domestic demand deposit pricing relative to fed funds rates. Each plot presents the industry and average measure in a tightening cycle and in loosening cycles where the shaded regions are defined as tightening cycles. Deposit sensitivity measures are suppressed when the fed funds rate is < 50bps to remove extreme values at very low fed funds rates that are not relevant at longer maturity horizons. The average fed funds rate in the quarter is also plotted. Figure IA15a plots the implied deposit rate to the average FF rate; Figure IA15b relative to demand deposits and the implied demand deposit rate. Both plots consider the industry (solid lines) and the average (dotted lines).

(a) B^R : Ratio **(b)** B^C : Cumulative

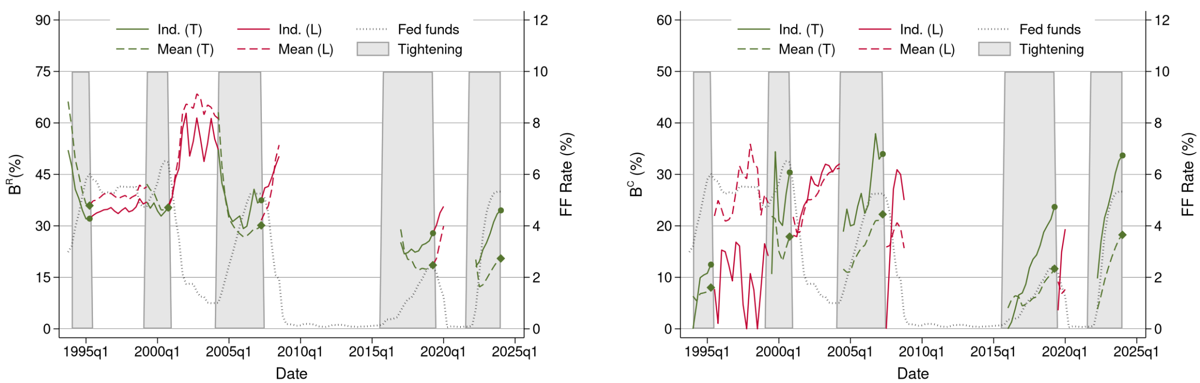


Table IA10 summarizes the tightening cycles and deposit behavior. These cycles vary in their length, the ultimate level of interest rates and the change in the Fed funds rate. In addition, there is significant heterogeneity in the sensitivity of deposit rates across banks and the growth in demand deposits. The interquartile range of the deposit to fed funds ratio is roughly two-thirds that of the average ratio, 29.6, 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 can reflect the significant heterogeneity observed in the data.

With respect to deposit behavior, our preferred sensitivity is the ratio of deposit rates to the fed funds rate, B^S, although we will show that cumulative changes load on similar bank characteristics.[7] 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 200% when the fed funds rate is less than 25bps, but otherwise the median sensitivity ranges from 40 to 46 and is not monotonic with the fed funds rate. The relevant forward rate beyond five years never falls below 1.9%, hence our long-term beta estimates appear reasonable as the extremely low rate environments are not empirically relevant for long-term valuation. When we extrapolate near term betas in Equation 16 we will make adjustments for periods with expected rates less than 25bps.

[7]The estimates that result from cumulative changes are more extreme and less consistent with observed behavior, particular during changing rate environments this initial rate appears to move slowly relative to conditions and pollutes long-term expectations with short-term asynchronicity.

Table IA10: Summary statistics for domestic demand deposit behavior 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), the three measures of relative deposit pricing, and the annual log growth rate in demand deposits over the cycle. The two deposit pricing measures include a ratio of deposit rates to the fed funds rate, B^R, and the total change in deposit rates relative to the change in the fed funds rate, B^C. 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	B^C	Growth
1993q4-1995q2	6.02	3.03	2.17	0.17	35.91	8.01	-1.00
			0.65	0.45	10.68	11.96	10.91
1999q2-2000q4	6.47	1.73	2.32	0.27	35.34	17.90	7.67
			0.97	0.52	14.48	28.91	11.63
2004q2-2007q2	5.25	4.24	1.67	0.94	30.13	22.22	4.46
			1.15	0.94	20.18	22.28	10.04
2015q4-2019q2	2.40	2.24	0.45	0.26	18.56	11.68	5.42
			0.40	0.33	16.54	14.80	6.81
2021q4-2024q1	5.33	5.25	1.10	0.96	20.49	18.25	-2.28
			1.06	1.01	19.62	19.28	8.14
Average	5.30	3.17	1.68	0.47	29.66	15.18	2.93
			1.44	0.69	19.14	21.40	10.97

Table IA11: The level of fed funds rates and 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.

	Mean	Median	p5	p95	N
$\leq 25bps$	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

C.4 Estimated betas

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

$$B_{i,T} = \alpha + \mathbf{\Gamma X}_{i,T} + \lambda \delta_{i,T} + \mathbf{\Theta Z}_t + \varepsilon_{i,T}, \tag{17}$$

where the ultimate sensitivities for each bank, $B_{i,T}$, are regressed on bank characteristics at the start of the cycle, $\mathbf{X}_{i,T}$, the annual change in log deposits at the end of the cycle, $\delta_{i,T}$, and cycle characteristics, $\mathbf{Z}_t$, such as the length of the cycle, the change in rates and the ultimate level of interest rates. We also run this regression including time fixed effects and then bank fixed effects to confirm that our cross-sectional and time-series variables are robust to specifications that absorb cycle- and bank-specific differences. The fixed effects specifications do not allow us to generate predictions as they exclude relevant time-series factors and banks that enter or exit over time.

Estimation of the relation between pricing and quantities (i.e., sensitivities and growth) is subject to simulteneity bias. The growth coefficient in particular may be attenuated, as we are estimating this relation in reduced form. We will find that growth is positively correlated with pricing, consistent with an upward sloping supply curve (depositors supply more deposits to banks with higher rates) at various levels of bank demand for deposits (see Figure IA16). If banks face a common supply curve that is stable over time, then for a given cycle we are simply recovering various points on the supply curve. However, if bank supply curves vary in the cross-section or time series then the estimates of deposit growth may be attenuated by the fact that a higher supply curve (i.e., higher growth) will result in lower prices. Given the positive relation in our regressions, our objective to assess bank solvency, and the fact that more than 90% of banks exhibit growth rates in excess of our drawdown rate, the potential attenuation of this coefficient typically results in a more conservative (i.e., higher) betas. 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).

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 depositors, 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 the size of accounts and the depositor relationship with the bank corresponding to the type of depositor (retail, high net worth retail, corporate, etc.) (Luck and Plosser, 2024). For instance, the average size of deposit accounts is positively related to deposit pricing and the share of 'small' accounts is negatively related.[8] Additional factors such as bank size, deposit HHI, and 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

[8]These variables are correlated with the share of typically insured deposits but not exactly. The distinction ties pricing behavior to deposit size rather than insurance coverage which varies over time.

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 rise with rates. For both variables we use the natural logs as the relations are nonlinear.

The coefficient estimates from our regressions are summarized in Table IA13. Columns (1) and (4) are the models used to predict long-term betas, as they exclude fixed effects. We find that initial deposit rates, the size of accounts and their concentration in bank branch networks increase the ultimate sensitivity of deposits to rates. Deposit growth is positively correlated with pricing, consistent with higher rates attracting more deposits. 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) and (5) the cross-sectional coefficients remain similar in their magnitude and statistical significance and there is little change in adjusted R-squared. When we include bank fixed effects in columns (3) and (6), the coefficients for the ratio, B^R, are roughly the same, although we do obtain additional explanatory power suggesting that additional bank controls may further improve these estimates.

We use the coefficients from these models to generate long-term estimates of deposit betas for each bank, i, and quarter, t. To do so, we seed the regression with bank characteristics, $\mathbf{X}_{i,t}$ and the constant drawdown rate of 5%, δ.[9] We also include time-varying factors, $\mathbf{Z}_t$: a constant cycle length of 12 quarters and the actual 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.

$$\widehat{B_{i,t,}} = \hat{\alpha} + \widehat{\mathbf{\Gamma}}\mathbf{X}_{i,t} + \widehat{\lambda}\delta + \widehat{\mathbf{\Theta}}\mathbf{Z}_t, \tag{18}$$

We map our predicted deposit rate sensitivities into our valuation equation using our estimates of B and the risk-neutral forward rate at the 5- to 10-year horizon:

$$\beta_{i,t}^R = \widehat{B_{i,t}^R} \tag{19}$$

$$\beta_{i,t}^C = \frac{r_{i,t}^D + (f_t^{5-10} - ff_t)\widehat{B_{i,t}^C}}{f_t^{5-10}}. \tag{20}$$

The implied betas are bounded in the range 0 to 100, inclusive.

Figure IA15 shows the distribution of implied betas based on the coefficients in Columns (1) and (4) of Table IA13. The two approaches yield similar estimates and dynamics. The betas based on ratios are slightly lower than the cumulative betas in the pre-GFC period and slightly lower in the post-period. Our preference for the ratio betas, β^R, is based on their

[9] 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 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.

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. *Retail share* is the percent of deposits in branches designated as full service retail branches and excluding main offices, which aggregate non-retail deposits, for branch networks greater than 15. ln*(Liquidity/Deposits)* is the log of the ratio between cash and securities and total deposits winsorized at the top 100bps. *Deposit growth* is calculated as the per annum change in log deposits over the cycle.

	N	Mean	Med.	SD	Min	Max
Deposit sensitivities						
B^R: Ratio (%)	29,912	29.65	30.05	14.61	0.00	85.72
B^C: Cumulative (%)	29,912	15.18	10.51	16.35	0.00	100.00
Bank controls						
Dep. rate/f^{5-10} (%)	29,912	30.40	29.60	22.49	0.00	98.92
Deposits/Account ($ '000s)	29,912	25.10	18.19	22.75	0.02	209.25
NIB share (%)	29,912	28.63	27.60	12.94	0.00	100.00
Small acct. share (%)	29,912	67.89	69.66	17.60	0.00	100.00
MMDA share (%)	29,912	25.17	22.15	17.72	0.00	100.00
Deposits/Branch ($ mm)	29,912	73.34	56.12	62.23	0.07	596.35
Retail share (%)	29,912	98.00	100.00	7.82	0.00	100.00
ln(Liquidity/Deposits)	29,912	4.12	4.15	0.57	0.05	5.71
Deposit growth (%)	29,912	2.93	1.64	11.51	-30.68	70.31
Time-series controls						
ln(Cycle length)	29,912	2.13	2.20	0.35	1.79	2.64
ln(ff_T) (%)	29,912	1.62	1.67	0.33	0.87	1.87
Cycle length (Quarters)	29,912	8.93	9.00	3.21	6.00	14.00
Δff_T (%)	29,912	3.17	3.03	1.21	1.73	5.25
ff_T (%)	29,912	5.29	5.33	1.34	2.40	6.47
f^{5-10}	29,912	3.49	3.14	0.63	2.76	4.40

reduced sensitivity to lift-off deposit rates that tend generate volatility when interest rates are moving quickly and deposit rates have yet to recognize them. Overall, the correlation

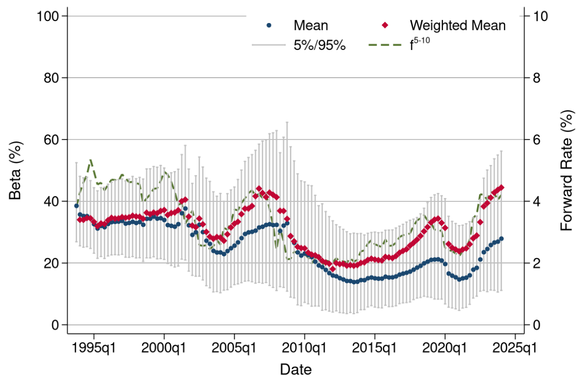
Table IA13: Regression: Domestic deposit sensitivities in hiking cycles. This table reports the estimated coefficients from regressions of bank deposit sensitivities on bank and time-series controls for 5 hiking cycles. Results for the ratio of deposit rates to the fed funds rate, B^R, are in columns (1) through (3) and results for the cumulative change in deposit rates relative to the cumulative change in fed funds rates, B^C, are in columns (4) through (6). Bank controls are as of the first quarter of each hiking cycle. Columns (2) and (4) include time fixed effects and (3) and (6) bank fixed effects. Standard errors are clustered by date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	B^R			B^C		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. rate/f^{5-10} (%)	0.52***	0.55***	0.45***			
	(0.03)	(0.05)	(0.04)			
Deposits/Account ($ '000s)	0.09***	0.09***	0.09***	0.07**	0.07**	0.06**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
NIB share (%)	-0.17***	-0.15***	-0.11***	-0.15***	-0.15***	-0.04
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Small acct. share (%)	-0.08**	-0.08**	-0.10***	-0.15***	-0.14***	-0.14***
	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
MMDA share (%)	0.08***	0.08***	0.06**	0.12***	0.12***	0.07*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
Deposits/Branch ($ mm)	0.02***	0.02***	0.03***	0.02***	0.02***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Retail share (%)	-0.06**	-0.06*	-0.06**	-0.07**	-0.07**	-0.07*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
ln(Liquidity/Deposits)	-2.27**	-2.18**	-2.33***	-2.67***	-2.77***	-2.30***
	(0.70)	(0.61)	(0.23)	(0.57)	(0.55)	(0.25)
Deposit growth (%)	0.26**	0.27*	0.25**	0.48***	0.44**	0.42***
	(0.09)	(0.10)	(0.06)	(0.09)	(0.11)	(0.05)
ln(Cycle length)	12.10***		0.00	12.86***		
	(1.89)		(0.00)	(2.76)		
ln(ff_T) (%)	9.76***			18.24***		
	(0.54)			(0.98)		
Observations	29912	29912	26198	29912	29912	26198
Adj. R^2	0.63	0.63	0.73	0.33	0.34	0.48
Fixed Effects	No	Time	Bank	No	Time	Bank
Y mean	29.65	29.65	28.90	15.18	15.18	15.34

between these projected rates is greater than 0.9. A more structural approach could further refine the estimation and improve upon the joint problem of determining price and maturity.

Figure IA15. Estimated long-term betas. These figures plot the distribution of implied demand deposit betas at a five-year horizon conditional on a 5% deposit drawdown rate and prevailing 5-10 year risk neutral forward rates. The figure also includes the forward rates.

(a) β^R : Ratio



(b) β^C : Cumulative

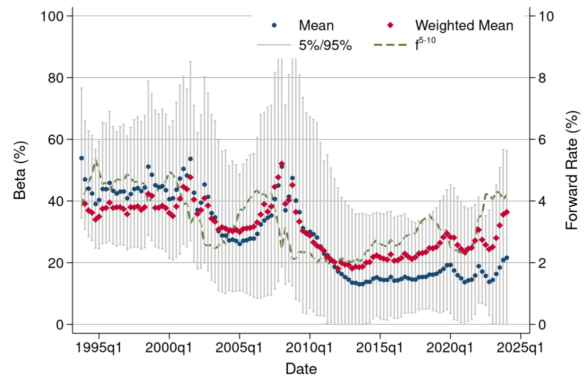
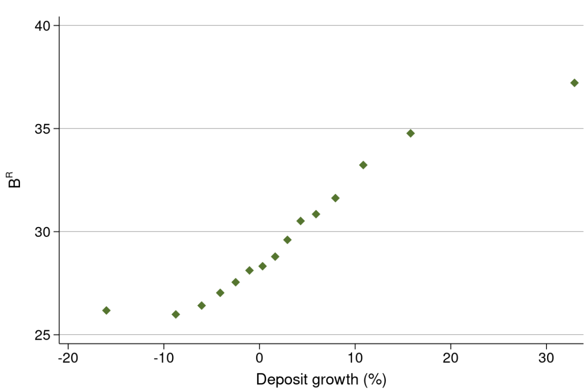
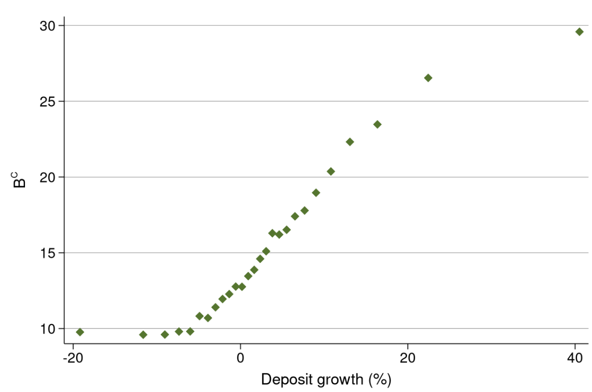


Figure IA16. Binscatter: Deposit sensitivities and deposit growth. These figures plot ultimate deposit sensitivities (B^R and B^C) versus deposit growth over a hiking cycle conditional on the control variables in Table IA13 Column (2). Bins are data-driven as per Cattaneo et al. (2024).

(a) β^R : Ratio



(b) β^C : Cumulative



C.5 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, we also restrict our focus to ratios, B^R, rather than also estimating cumulative sensitivities.

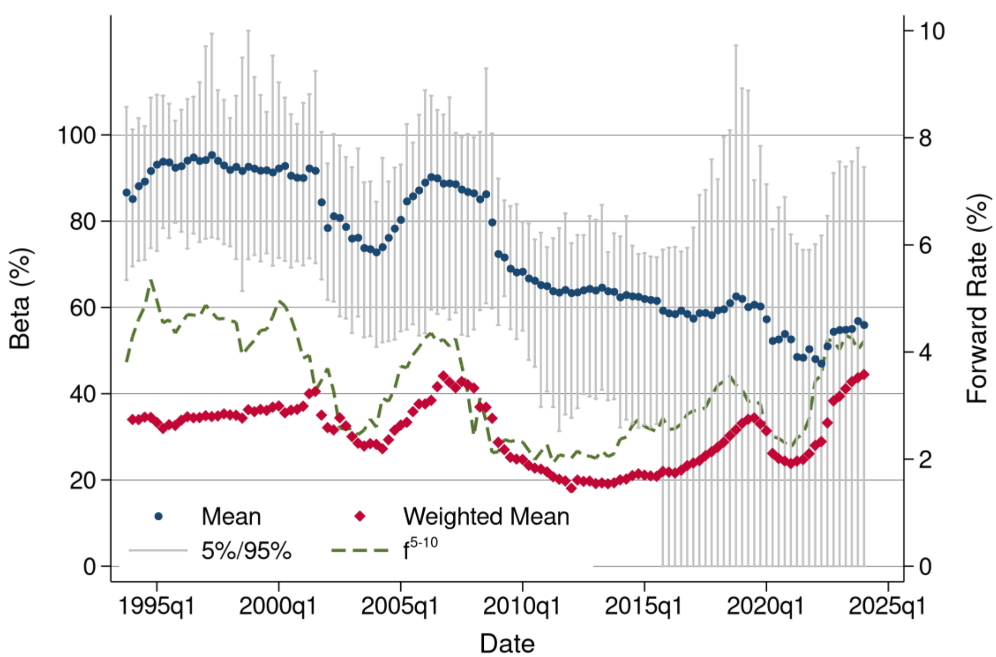
Table IA14: Summary statistics for estimates of foreign deposit rate sensitivities. This table reports the summary statistics for the variables used to estimate foreign demand deposit sensitivities over a hiking cycle. Deposit sensitivities are as of the end of a hiking cycle whereas bank controls are 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	83.92	88.41	37.43	0.00	282.08
Bank controls						
Dep. rate/f^{5-10} (%)	347	65.56	67.09	46.46	0.00	201.54
NIB share (%)	346	7.27	0.00	19.10	0.00	100.00
ln(Liquidity/Deposits)	347	4.04	3.99	0.54	2.66	5.71
Time-series controls						
$\ln(ff_T)$ (%)	347	1.69	1.79	0.27	0.87	1.87
f^{5-10}	347	3.65	3.81	0.59	2.76	4.40

Table IA15: 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, B^R. Bank controls are as of the first quarter of each hiking cycle. Column (2) includes time fixed effects and (3) bank fixed effects. Standard errors are clustered by date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)
Dep. rate/f^{5-10} (%)	0.26**	0.18***	0.16
	(0.08)	(0.03)	(0.10)
NIB share (%)	-0.72***	-0.63**	-0.58*
	(0.14)	(0.16)	(0.22)
ln(Liquidity/Deposits)	-1.77	-2.52	-0.17
	(3.01)	(3.18)	(3.40)
$\ln(ff_T)$ (%)	8.73		-0.34
	(8.93)		(9.31)
Observations	346	346	248
Adj. R^2	0.33	0.36	0.37
Fixed Effects	No	Time	Bank
Y mean	83.86	83.86	81.60

Figure IA17. 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

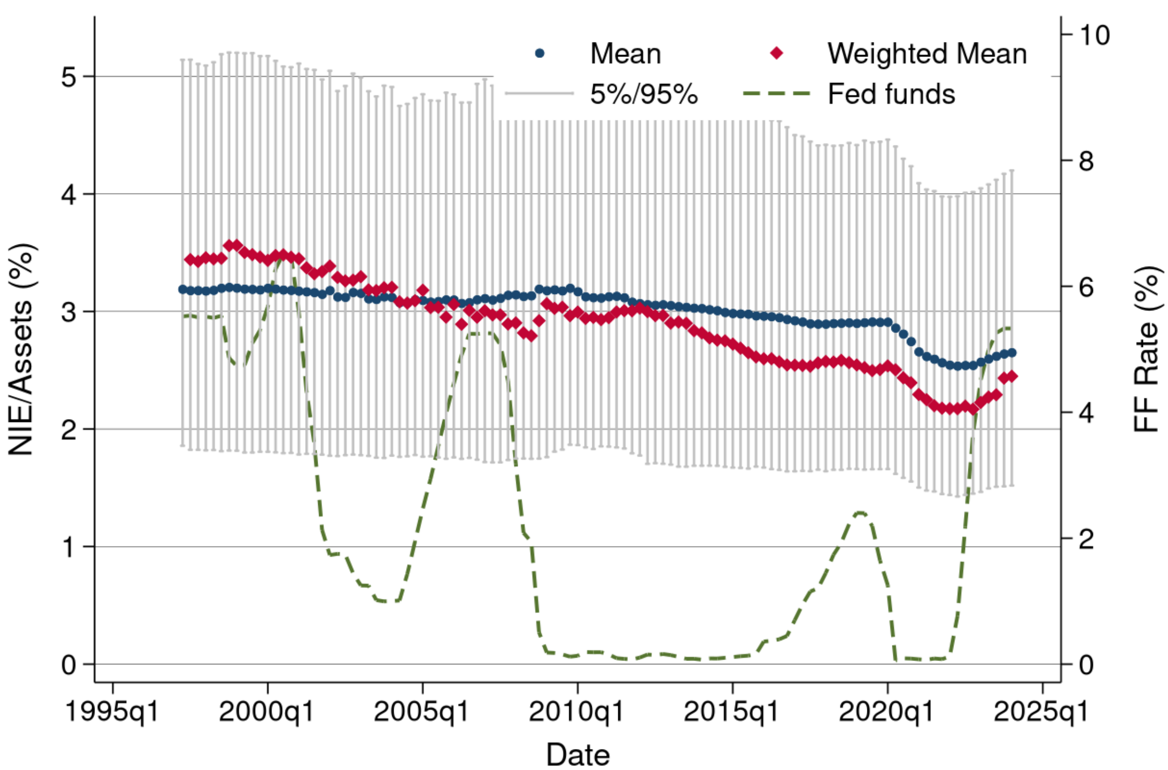
As with deposits, we incorporate the expense perpetuity, Equation 5, into a valuation equation that includes the slope of near term discount rates. The present value of expenses per dollar of assets:

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

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%), real estate loans, and non-real-estate 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 IA18. 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 5-year risk neutral forward rate.



D.1 Necessary expenses

Our objective is to estimate the necessary expenses a typical bank must expend to realize the value of their assets 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 would still like estiamte necessary expenses that reflect bank-specific characteristics, as expenses can vary by bank size, business mix, and depositor type. 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. Table IA16 summarizes the the regression variables. 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, $\overline{Assets}$. To reduce the influence of outliers on our estimation, we bound the NIE ratio on the left at 35bps (which is less than the first percentile) and at the 99th percentile. For other revenue ratios we winsorize at the top and bottom 50bps. 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 IA17 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, t he results were not materially different and so we rely on this parsimonious approach.

We use this empirical model to generate a standardized prediction of a bank's necessary expenses based on their underlying characteristics. We seed other noninterest income and income from sales to zero to remove expenses related to fee-based franchises and one-time events. This is consistent with the fact we exclude these franchises from our valuation. 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. We do this to exclude expenses related to the value creation of loans (i.e., value in excess of book at origination). 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 income level of loans. For similar reasons, we set expenses associated with loan loss reserves to zero. For all other right hand side variables, we use the ratio at t to generate a necessary expense ratio for each bank-quarter. 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,

Table IA16: 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 2004: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 such as 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	576,912	2.94	2.81	0.98	0.35	9.57
Income controls (/Assets)						
Int. Inc.	576,912	5.30	5.07	1.58	1.29	13.54
Int. Exp.	576,912	1.67	1.38	1.22	0.02	5.53
Other NII	576,912	0.39	0.25	0.64	-0.13	15.08
Inc. from sales	576,912	0.07	0.00	0.36	-1.57	10.18
Deposit fees	576,912	0.30	0.24	0.24	0.00	1.74
Deposit controls (/Assets)						
Non-IB dep.	579,047	14.27	12.51	9.73	0.00	100.00
IB dep.	579,047	67.03	67.99	10.14	0.00	100.00
Branches	576,912	0.25	0.21	0.16	0.00	3.30
B/S controls (/Assets)						
Fixed assets	579,047	2.05	1.47	6.07	0.00	100.00
Loans	579,047	59.84	61.55	14.49	0.00	100.00
Loss Reserves	579,047	1.25	0.80	6.03	0.00	100.00
Cash & Securities	579,047	29.72	27.30	15.63	0.00	100.00
Other controls						
log(Assets)	579,047	5.61	5.38	1.22	3.91	15.14

and bound these estimates at a minimum of 35bps and a max of 3% (overall these bounds impact <1% of estimates). The distribution of estimates over time is depicted in Figure 5a.

Table IA17: 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 IA16. 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.	-0.32***
	(0.02)
Other NII	0.67***
	(0.02)
Inc. from sales	0.78***
	(0.03)
Deposit fees	0.85***
	(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	576912
Adj. R^2	0.63
Y mean	2.94

E Results

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

Figure IA19. 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 $< 3\%$).

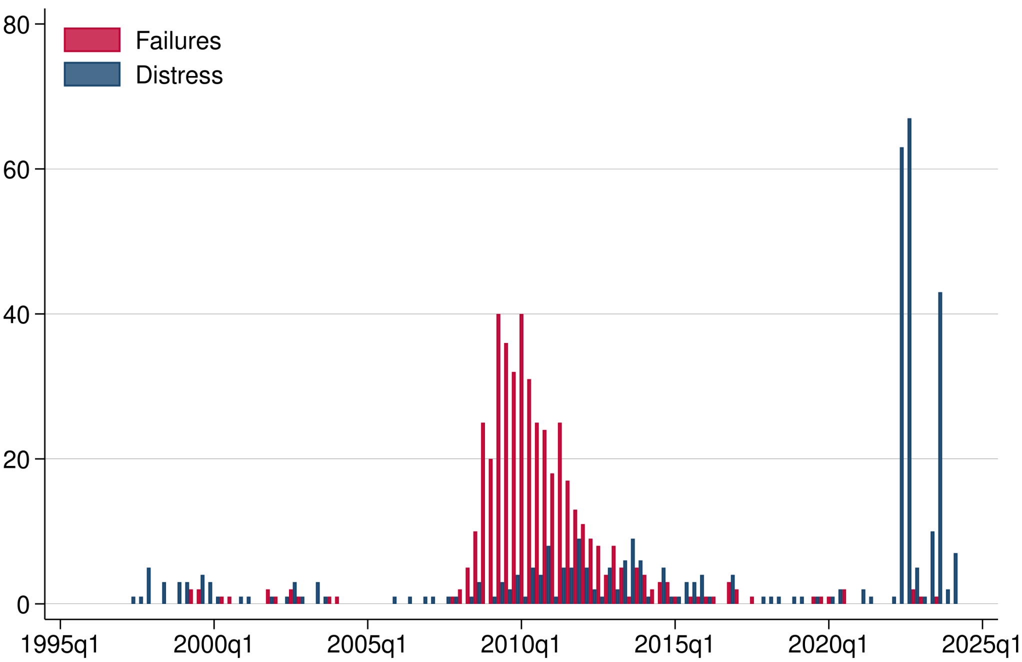
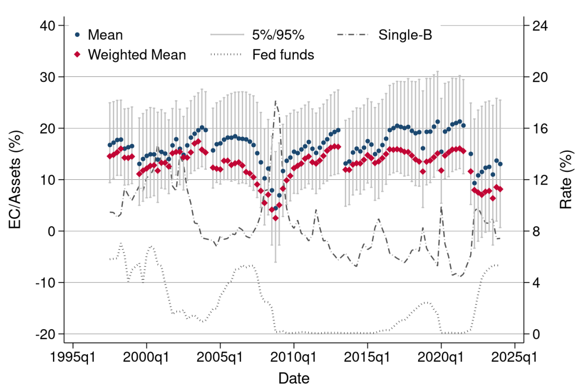


Figure IA20. Distribution of R-EC in response to stress. These figures plot the distribution of R-EC from 1997:Q2 to present. Figure IA20a the R-EC in a 250bps parallel shock to interest rates scenario. Figure IA20b theR-EC where the risk spreads increases by 250-500bps. Each chart includes the 5th-95th percentile, the average and the weighted average as well as the single-B yield and the fed funds rate.

(a) Risk-free rates



(b) Credit spreads