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ABSTRACT

This paper measures interest rate and credit risk exposures in U.S. banks' fixed-income positions over the last 30 years. We exploit the factor structure in fixed-income returns to represent banks' positions, including derivatives, as simple portfolios. The typical bank is long both risk factors, with interest-rate exposure from derivatives reinforcing that from other business. Until recently, interest-rate exposure hedged credit exposure in times of stress. The 2022-3 crisis was special because both risk factors performed poorly at the same time, hurting especially less-regulated small banks that had built up both exposures. Banks also systematically increase interest-rate risk exposure ahead of low excess returns on long bonds, which we show to be consistent with a liquidity-centric business model.

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1 Introduction

Macro finance research has recently focused on the relationship between asset prices and risk exposures of intermediaries, especially banks.[1] While traditional asset pricing theory links prices to macroeconomic fundamentals such as consumption and inflation through optimal household behavior, recent work relates prices to banks' risk exposures through their optimal portfolio strategies. Similarly, much discussion of financial crises and the role of central bank asset purchases revolves around changes in private banks' risk exposures.

A challenge for evaluating new theories and assessing policy is that banks' risk exposures are difficult to measure. This is not for lack of raw micro data: banks are required to supply accounting measures for a large number of fixed-income positions that differ in maturity and credit quality. However, there is no consensus way to summarize risk exposures contained in bank portfolios. Can this vast amount of information be compressed to discuss banks' portfolio dynamics, for example, in response to policy, in a parsimonious way?

This paper represents the entire risk exposure of a bank's fixed-income position as a simple portfolio. Our starting point is that only two risk factors—asset returns that isolate interest rate and credit risk—account for the overwhelming majority of quarterly return variation in any instrument held by banks. For any balance-sheet position, we can thus construct a simple portfolio with very similar risk characteristics. We find factor exposures—dollar values invested in each factor asset—that move with factors exactly like the position itself. To match the overall position value, we add a residual amount of cash.

We then use this methodology to develop a set of new stylized facts about bank risk that can serve to assess models and guide policy discussion. We replicate the *net fixed-income position*, that is, fixed-income assets less fixed-income liabilities, for every public US bank holding company between 1995 and 2024. Our risk exposure measures are easy to compare and aggregate across positions or banks. In particular, we compare exposures in a bank's derivatives book to its other business and assess the contributions of different size groups to aggregate risk. By subtracting the value of the net fixed-income position and its net nonfinancial assets from the bank's stock market value, we also obtain a new measure of bank franchise value.

Our interest-rate risk factor is the return on a five-year bond without default risk. This factor is low when the yield curve shifts up. Our credit-risk factor is the return on a leveraged portfolio

[1]For example, this theme is common to intermediary asset pricing models in the tradition of He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014) or Vayanos and Vila (2021)), demand systems for intermediaries following Koijen and Yogo (2019) as well as the literature on monetary policy and bank regulation based on Gertler and Karadi (2011).

that is long a five-year BBB-rated bond and short a five-year default-free bond. This factor is low when credit spreads widen. During 1995-2024, the average net fixed-income position of US public banks was worth 6% of assets, slightly below book equity at 9%. It was equivalent to a long position in interest-rate risk worth 25% of assets, a long position in credit risk worth 7%, and a 26% short position in cash. Averages mask large heterogeneity in the cross section and over time. As one example, at the end of 2021, Silicon Valley Bank held interest-rate risk worth 42% of assets, or 5.4 times book equity.

We present four main findings. First, once banks were allowed to combine broker-dealer and traditional banking business after 1994, the extra interest-rate risk exposure from securities and derivatives was positive: it reinforced, rather than hedged, exposure from traditional maturity mismatch. On the eve of the 2008 crisis, the large universal banks stood out for their large interest risk exposure, both historically and relative to smaller traditional banks. This stance actually served them well in the crisis: when the Fed aggressively cut rates, gains from securities and derivatives partly hedged losses from credit risk in the loan portfolio.

Second, after the 2008 crisis, large universal banks reduced credit risk, whereas smaller, less regulated, traditional banks became more risky. On the eve of the 2022 crisis, the special feature of big banks was their low credit risk exposure. In contrast, mid-sized banks—exempted from stress testing and resolution planning by the 2018 Dodd-Frank rule rollback—stood out for their higher credit-risk exposures and interest-rate risk exposures from securities and derivatives. Regarding interest-rate risk specifically, small and large banks thus became more similar after the crisis. In the Covid recession, when factors again comoved negatively, all banks profited from the hedge provided by interest-rate risk.

Third, the 2022-3 banking crisis was special not only because of large losses on interest-rate risk positions but also because credit-risk positions performed poorly at the same time, in sharp contrast to previous episodes of stress. The shift in factor correlations from negative to positive coincides with a switch in the bond-stock beta. We similarly document an unusually close comovement between banks' stock market values and their net fixed income positions, whereas franchise values moved relatively little, in contrast to their earlier behavior.

Finally, larger interest-rate risk exposure relative to assets predicts *lower* excess returns on long bonds over the next year. This finding is puzzling from a pure portfolio choice perspective: banks appear to mistime the market systematically. It is consistent, however, with a desire to smooth net interest margin (NIM). To show this, we use our framework to decompose changes in risk exposure into capital gains and trades. Banks actively buy risk exposure ahead of low excess returns, especially when interest rates are low and deposits flow in. When interest rates subsequently rise, interest expense tends to respond slowly due to sticky deposit rates, so a longer-duration asset portfolio that is similarly less rate sensitive stabilizes NIM.

Our results deliver some general takeaways for modeling banks. First, it is important to jointly analyze credit and interest rate exposures. For example, the 2008 crisis was not only about credit risk, and the 2022 crisis was not only about interest-rate risk. Second, the fact that two risk factors work well means that joint modeling is easier than one might have thought. Even exposure of complex portfolios with many distinct assets can be expressed in terms of two contingent claims positions. This does not mean, however, that bank portfolio choice is frictionless: rents from market making and deposits, as well as frictions that encourage income smoothing, are nevertheless crucial for understanding banks' risk dynamics.

We also draw two lessons for regulation. First, we can use our exposure measures for scenario analysis, akin to stress testing: for any scenario of factor realizations, we can project portfolio income forward from an initial set of exposures. To illustrate this idea, we compare 9-quarter projections based on December 2020 exposures to the Fed's stress test projections from that date.[2] We show that our approach would have correctly flagged the vulnerability of relatively smaller and more traditional banks already then. Since our projections rely only on public data and are transparent and simple enough to be produced quickly for many banks and scenarios, they can complement existing, more detailed approaches.

Second, we caution against exposure measures based on time-series regressions, especially those using bank stock returns. In general, identifying exposures with regression coefficients works only if they remain constant over time. Our measures, in contrast, pick up variation in exposure at high frequencies directly from balance-sheet data each period—we do not rely on a stable relationship between fixed-income positions and asset returns. Exposure measures from stock return regressions require in addition a stable relationship between non-fixed-income positions, such as franchise value, and asset returns. We use the 2022 crisis to illustrate how the unusual comovement of factors and stock market values can lead regression measures astray.

Our calculations proceed in two steps. We first find exposures for many fixed-income instruments by regressing their returns on risk factors. This step uses only data on returns, not on bank positions. The regression coefficients measure the factor exposures of one dollar invested in the instrument. For most maturities and credit qualities we consider, R^2s are above 80%. We further find that the residuals from these regressions are close to homoskedastic: time variation in the volatilities and correlations of any two individual bond returns comes mostly from the dynamics of the risk factors. We can therefore capture time-varying second moments in bond returns well,

[2] For an overview of how stress tests are used in US regulation, see Board of Governors (2024).

even if we work with a fixed set of regression coefficients to measure exposures.

In a second step, we add data on bank positions. Every position implies a payoff stream that we can value as a portfolio of bonds, and then replicate. Our implementation draws on publicly available data from the U.S. Reports on Bank Conditions and Income (the "call reports"). The computations are easiest for positions such as securities for which banks report market values on their balance sheet. For loans and long-term debt, banks report face values, not market values. We derive payment streams from data on maturity or time-to-repricing as well as regulatory measures of credit quality. We define bank franchise value as the stock market value less the (net) fixed-income and non-fixed-income positions from the balance sheet.

A key advantage of our portfolio approach is that it is also conceptually straightforward to compute exposures through derivatives positions. A challenge for implementation is that, for interest-rate derivatives, we observe only total market values but not the direction of trading or payoff details.[3] We propose an estimation strategy that infers risk exposures of a position from the comovement of its fair value with interest rates. The basic idea for identification is that if fair value increases when rates fall, it is more likely that the bank placed a bet on falling rates, as with a pay-floating swap. Moreover, the size of the gains reflects the magnitude of the position's exposure to interest-rate risk.

It is possible, in principle, that banks face important risk factors beyond those we consider—for example, fluctuations in deposit or loan spreads that reflect liquidity conditions or markups, or volatility in particular sectors or regions. If such additional factors are important, we should see significant variation in bank income unrelated to either our factors or the bank portfolio decisions we model. To check this, we define a bank's *portfolio income* as the return on its replicating portfolio from our approach, as well as *accounting portfolio income* as the sum of net interest income and reported capital gains from banks' income statements.

We find that portfolio income and accounting portfolio income are highly correlated in the time series, even at the individual bank level. In particular, correlation coefficients for large banks are in the same ballpark as correlations between instrument returns and factors. The factor structure in instrument returns is therefore the major driver of bank income volatility as well. Portfolio income is naturally more volatile than accounting portfolio income since it includes all unrealized capital gains, whereas accounting rules allow banks to smooth income. But we do not see that

[3]For example, when we observe a position with positive fair value at some date, we only know that the bank placed a bet that paid off up to that date, but not whether it was a bet on interest-rate increases (for example, a pay-fixed swap) or decreases (a pay-floating swap). This is in contrast to the reporting for credit-default swaps, where call report data contain information on market and notional values separately by whether protection is bought or sold, so replication is straightforward.

smoothed accounting income contains a large component of gains and losses that is orthogonal to our factors.[4]

Related literature. Our methodology is based on a large body of work on the properties of fixed-income asset returns (for a survey, see Piazzesi 2010). It is well-known that prices of similar fixed-income instruments move closely together, the basic fact behind our replication strategy. In other words, the factor structure in fixed-income returns is very strong, much more so than, say, in the stock market. Some other papers have exploited a factor approach to simplify portfolios. Piazzesi and Schneider (2010) consider interest-rate risk in household portfolios. Koijen, Van Nieuwerburgh and Yogo (2016) study household demand for insurance and summarize insurance products by the degree to which they hedge effects of adverse health and mortality on wealth. Jiang, Lustig, Van Nieuwerburgh and Xiaolan (2024) study government debt. Our contribution is to represent the portfolios of individual banks along their two most prominent dimensions, interest rate and credit risk, combining exposures from all their fixed-income instruments, including derivatives.[5] More generally, we provide a novel way to measure risk exposures that can also help represent asset quantities for other market participants.

Studies of intermediaries' asset demand for fixed-income instruments often focus on demand for individual instruments, especially bonds (see, for example, Koijen, Koulischer, Nguyen and Yogo 2021, Bretscher, Schmid, Sen and Sharma 2025, Fang and Xiao 2025). The factor exposures we compute could be used directly as observable characteristics to capture risk in such studies. Since our exposures are additive, they aggregate conveniently to the portfolio level, similar to duration, but different from discrete characteristics like credit rating. Moreover, they reflect the comovement and hence hedging properties of returns, while duration and rating describe the marginal distribution of interest rate and credit risk, respectively.[6] Finally, the time-varying conditional distribution of factors can be used to distinguish periods where risk characteristics of positions change.

Dynamic models of intermediary asset pricing require a choice of how many and which assets

[4]Spreads charged by banks contribute to the average level of net interest income, but less to income volatility. Portfolio income even comoves significantly with raw accounting income, which contains lower frequency trends from the cost of variable inputs and loan loss provisions.

[5]Our approach for representing derivatives builds on Gorton and Rosen (1995) who also infer the direction of trading from banks' positions, but who did not yet have the data on fair values that allows us to measure time-varying exposures.

[6]For example, while we use ratings or capital weights as indicators of credit quality, we do not map them one-for-one into credit-risk exposures. Instead, our factor model implies that shorter positions are less exposed than longer positions with the same rating, since their returns covary less with the credit-risk factor. By the same token, there is no one-for-one mapping in our framework between interest-rate risk and simple measures of duration that ignore credit risk. Our replication instead takes into account that zero-coupon bonds of lower credit quality are less exposed to interest-rate risk for the same maturity.

to include. There is a long tradition of building models with incomplete markets and only a few assets, often selected for tractability. An alternative approach assumes complete markets for aggregate risks, so agents select exposures, while the choice of instruments to achieve that exposure remains indeterminate, or is mapped to a particular asset structure to fit the data. For example, Di Tella and Kurlat (2021) and Kekre, Lenel and Mainardi (2025) take this route to study the allocation of interest-rate risk between bankers and other agents. Other examples are the model of sovereign debt with many maturities in Dovis (2019) or the allocation of equity risk with heterogeneous households in (Chien and Lustig 2010). Our results suggest that a complete markets approach is fruitful for modeling banks since factor exposures capture bank risk and bank performance. Our replicating portfolios also provide direct inputs for calibration of models, for example in studies of bank regulation such as Elenev, Landvoigt and Van Nieuwerburgh (2021) and Begenau, Landvoigt and Elenev (2025).

Our quantitative results contribute to a growing literature on recent trends in the U.S. banking industry, in particular leading up to the 2022 crisis. An important theme is that bank activity is shifting towards a business model centered around liquidity creation through money-like liabilities or credit lines (Gorton and Pennacchi 1990) and away from the traditional model where value comes from the screening and monitoring of borrowers. Consistent with a liquidity-centric model, banks now have more securities, fewer loans, but more deposits (Buchak, Matvos, Piskorski and Seru 2024, Hanson, Ivashina, Nicolae, Stein, Sunderam and Tarullo 2024), extend more credit lines (Acharya, Jager and Steffen 2023), and hold more liquid assets (Stulz, Taboada and van Dijk 2022). Jiang, Matvos, Piskorski and Seru (2024) measure interest-rate risk exposure in securities and loans ahead of the crisis. Our contribution here is to display the buildup to the crisis in two-dimensional risk exposure space, with credit risk as a key dimension. The increase in *both* exposures left small banks vulnerable to surprisingly correlated shocks in 2022.

Our findings on portfolio dynamics relate to an active literature on interest rate smoothing and deposit funding as key motives for bank portfolio choice. Flannery (1981) and English (2002) are early papers documenting that banks choose assets and liabilities to insulate their net interest margin and hence profits from interest rate fluctuations. Di Tella and Kurlat (2021) derive an optimal portfolio with maturity mismatch from the intertemporal hedging demand of a banker with a deposit franchise and a strong enough desire for income smoothing. Deposits as customer capital are further studied by Jermann and Xiang (2023), Gelman and MacKinlay (2024) and Bolton, Li, Wang and Yang (2025). One plausible reason for income smoothing is financial frictions. This perspective underlies work on how monetary policy affects risk taking via bank profits (for example, Gomes, Landier, Sraer and Thesmar (2021)). Our contribution is to present new facts on how overall portfolio risk exposures move with interest rates and show that income smoothing can rationalize why high risk exposure predicts low excess returns.

Our focus on bank portfolios distinguishes our exposure measures from stock-return betas, the coefficients in regressions of bank stock returns on risk factors. (see Acharya, Brunnermeier and Pierret (2024) for a review). Importantly, a bank's stock market value consists of not only its fixed-income position but also its franchise value which contains the present value of rents from equity adjustment costs (Gertler and Karadi 2011), bailout guarantees (Kelly, Lustig and Nieuwerburgh 2016), the market-making franchise (e.g., Lagos and Rocheteau 2007, Duffie 2017), Atkeson, d'Avernas, Eisfeldt and Weill 2019), the deposit franchise (Drechsler, Savov and Schnabl 2021) or the combined deposit and lending business (DeMarzo, Krishamurthy and Nagel (2025)). While the literature has proposed measures of various components of franchise value, our approach implies a residual measure of overall franchise value for each bank. We show that the dynamics of this measure changed the stock-bond correlation for banks in 2022, so stock-return regressions would have delivered poor measures of risk exposures before the recent crisis.

The paper is structured as follows. Section 2 provides an overview of our approach. Section 3 describes the distribution of returns. Section 4 explains how we replicate positions and compares portfolio income to accounting measures. Section 5 presents the time series and cross-section of exposures and introduces our approach to stress testing. Section 6 relates exposures to subsequent excess returns. Section 7 provides a comparison with alternative risk measures.

2 Banks' fixed income portfolios

Bank balance sheets record many different fixed-income instruments, which are securities that promise streams of payments. Our goal is to derive risk measures for each instrument.

Risk factors. We study exposure to a set of risk factors that are common drivers of the asset returns earned by banks. We fix an investment horizon of one quarter and ask how the value of banks' balance-sheet positions responds to changes in risk factors over that horizon. Formally, consider some date t and a typical bank that owns many fixed-income instruments i. Let r_t^i denote the (net) return from holding instrument i from date $t-1$ to date t. The conditional distribution of r_t^i given date $t-1$ information depends on the price of instrument i and expectations of future payoffs.

Let f_t denote an $F \times 1$ vector of *factors*, returns that are uncertain given date $t-1$ information.

Without loss of generality, the return on instrument i can be written as

$$r_t^i = \alpha^i + \sum_{j=1}^{F} \beta_j^i f_{t,j} + u_t^i, \tag{1}$$

where u_t^i is uncorrelated with the risk factors f_t. The residual u_t^i captures risk specific to instrument i or other risk factors that are not made explicit in our analysis.

Replicating portfolios. The coefficient β_j^i describes the *exposure* of instrument i to the jth risk factor—how much the return r_t^i moves with a change in the risk factor $f_{t,j}$. Since factors are themselves returns, we can interpret the vector of coefficients β^i as weights of a portfolio that mimics the responses of instrument i to factor realizations. The gain or loss on a 1-dollar investment in instrument i in response to a factor realization $f_{t,j}$ is the same as on a position of β_j^i-dollars in instrument j.

Consider a portfolio worth one dollar that puts weights β^i on the factors and the remaining weight $1 - \sum_j \beta_j^i$ on cash, a perfectly safe asset. Such a portfolio *replicates* instrument i at date t in the sense that it has the same conditional covariance with the factors as instrument i. This fact follows directly from forming covariances with factors f_t on both sides of (1). The remaining weight does not have to be literally cash but investments uncorrelated with the factors.

Bank risk exposures. We define the bank's (net) *fixed-income position* as the market value of its fixed-income assets less its fixed-income liabilities. Consider a bank position with a market value of V_t^i dollars invested in instrument i at date t. The value V_t^i is positive for positions on the asset side of the balance sheet and negative for positions on the liability side. We decompose this position into exposures $x_{t,j}^i$ to the various risk factors $j = 1, \ldots, F$ and a residual cash position:

$$x_{t,j}^i = V_t^i \beta_j^i \qquad \text{and} \qquad c_t^i = V_t^i \left(1 - \sum_{j=1}^{F} \beta_j^i\right).$$

Exposures are thus measured in dollars, just like the value of the position V_t^i itself, and can be positive or negative. Exposures are useful because they can be added across all instruments to obtain the $F \times 1$ vector of a bank's risk exposures $x_t = \sum_i x_t^i$. By summing over the subset of instruments i held in the derivative portfolio, we can determine whether the sign of that exposure is opposite to the exposure due to its traditional business. In this case, the bank uses derivatives to hedge other risk exposures. We can also compare exposures across banks or obtain the overall exposures of the banking sector.

While the loadings of a given dollar of exposure on the risk factors (i.e., β_j^i) are constant, the risk factors themselves evolve over time, and we allow their dynamics to change. As a result, even with fixed loadings, changes in factor dynamics induce time variation in a bank's position-level risk. Consequently, the implications of a given risk exposure for a bank's credit and interest-rate risk can shift over time.

Portfolio income. The *portfolio income* of a bank in period $t+1$ is the return earned on its (net) fixed-income positions between t and $t+1$. Using the risk factors f_{t+1} and the interest rate r^c_{t+1} on cash (known at date t), we define portfolio income as

$$y_{t+1} = f_{t+1}^\top x_t + r^c_{t+1} c_t. \tag{2}$$

Portfolio income is a *flow* which measures the income generated by the fixed-income positions of a bank. It measures the performance of the bank's portfolio in quarter $t+1$. With our measured exposures x_t, we can evaluate different performance scenarios by calculating portfolio income for different return realizations f_{t+1}. Our framework thus provides a simple approach to stress testing.

Given date t information, the only uncertainty in portfolio income y_{t+1} is due to the uncertain factor returns f_{t+1}. We can therefore compute the conditional distribution of portfolio income given a model of the factor dynamics. In particular, we consider the conditional volatility of y_{t+1} as a single summary statistic for risk faced by the bank at date t. Income risk measures are complementary to risk exposures since they represent a risk in flows that can be compared to the bank's income statement. In contrast, risk exposures are about risks in stock variables on banks' balance sheets.

Our concept of portfolio income is similar to accounting income as reported to regulators, although there are important differences. Most importantly, regulators do not require banks to mark all their positions to market. For large positions of the balance sheet, such as most loans and a substantial share of securities classified as "held-to-maturity", accounting income only contains interest income and not unrealized capital gains. In contrast, portfolio income (2) reflects the overall return consisting of both interest income and all capital gains. We compare these concepts in detail in Sections 4 and 5.3.

Inputs. Our approach requires two sets of inputs. First, we need the conditional distribution (1) of returns r^i_t for all instruments i. This is an exercise in asset pricing. We fit a statistical model to panel data on bond returns for different maturities and credit ratings that cover all instruments held by banks. The estimated slope coefficients β^i are sufficient for measuring exposures and studying income scenarios. We also estimate the conditional joint distribution of the factors f_t, which is useful to compute the conditional volatility of income. Second, we need market values

V_t^i for all relevant bank positions. We obtain them from regulatory filings when available. For positions not marked to market by banks, we develop market value proxies. The next two sections outline these steps.

3 The distribution of bond returns

Two stylized facts guide our bond return model. First, time-series regressions show that quarterly return variations for individual bonds are largely explained by two factors representing interest-rate risk and credit risk. Second, the regression residuals are nearly homoskedastic, indicating that the conditional return distribution, *given the factors*, is largely time-invariant. We first document these facts and then explain how they inform our choice of factors.

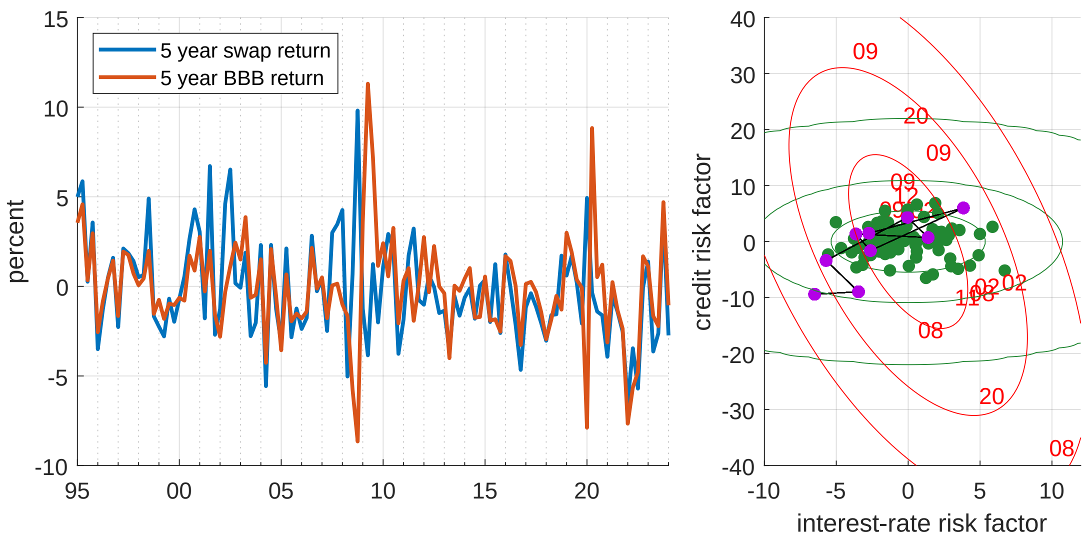
Bond return data. We assemble a panel data set of quarterly bond returns for the period 1990:Q2-2024:Q1. Returns on defaultable bonds come from Bank of America Merrill Lynch. From 1990 on, we have indices by maturity and credit rating. Returns take into account both price changes and default losses. Separate indices for mortgage-backed securities take into account prepayment options. We also use data on zero-coupon Treasury bond prices from the Federal Reserve Board, and returns on bonds priced off the swap curve, high-quality collateralized private claims traded in derivatives markets that are essentially default-free. Appendix A describes these data.

Returns on spanning bonds. We build factors from two *spanning bonds*, a 5-year swap quality bond and a 5-year credit-risky bond with a BBB rating. The left panel of Figure 1 shows that, for most of the sample, quarterly returns on the two spanning bonds move together, especially before the turn of the millennium and after 2015. Most of the time, bond returns reflect similar exposures to interest-rate risk due to their common duration of 5 years. Around the two major recessions, however, we see stark negative comovement. Both the 2007-9 financial crisis and the 2020 pandemic began with a spike in credit spreads and a drop in the short rate due to monetary easing. Consequently, the figure shows low BBB returns and high swap-quality returns. The pattern reverses as the recovery begins. We see similar patterns around smaller stress events in financial markets, such as the 2002 stock market downturn and the 2011 European debt crisis.

Factor structure in returns. Our first stylized fact is that the returns on the two spanning bonds account for most of the return variation in bank-held instruments. Securities and loans on banks' balance sheets are typically investment grade[7] (rated BBB or better.) Table A.1 in Appendix

[7]See Appendix B.2 for further details on the credit decomposition of bank assets.

Figure 1: Returns on spanning bonds



Notes: Left panel: times series of quarterly holding period returns for 5-year swap quality bond (blue) and 5-year BBB-rated bond (red). Right panel: scatter plot of quarterly realizations of interest-rate risk factor and credit-risk factor. Normal times are plotted as green dots, pre-2022 times of stress as text indicating the calendar year, and 2022:Q1-2024:Q1 as purple dots. Solid black line connects adjacent quarters. Contour lines are for normal density centered at the origin with the empirical covariance matrix of points in normal times (green) and pre-2022 times of stress (red).

A shows that, for all maturities, the R^2s in regressions of investment-grade bond returns on the two spanning-bond returns are around 90%. The return on the 5-year swap-quality bond alone explains above 70% of the return variation of all maturities.[8]

Homoskedastic residuals. We compute the p-value of the Engle test for heteroskedasticity of the residuals u_t^i in equation (1). The last column in Table A.1 in Appendix A shows that we cannot reject the null of no conditional heteroskedasticity for all bond returns, except for short-term Treasuries and swap-quality bonds. However, the risk in these short-term bonds is minimal, so any extra time-variation in the volatility of their returns will not affect our assessment of banks' portfolios below. Importantly, this does not imply that returns are unconditionally homoskedastic, since the conditional volatility of the factors themselves varies over time. The key property is that conditional heteroskedasticity in bond returns is mostly driven by conditional heteroskedasticity in factor returns but not by time variation in exposures of the individual bonds. Section 7.1 captures this time-variation in volatilities with a regime-switching model to interpret bank portfolio choice.

[8]We do not need to take a stand on what accounts for the remaining variation. Since our approach employs a linear framework, the results are valid regardless of where the additional variation comes from and would also be relevant if other factors were added later.

Selection of risk factors. We define the first factor as the return on the 5-year swap-quality bond. Since swap-quality bonds are essentially default-free, this factor captures movements in the level of safe interest rates. We refer to it as our *interest-rate risk factor*. Positive exposure to interest-rate risk corresponds to a long bond position. A bank or instrument with positive exposure to interest-rate risk loses money when rates on default-free bonds rise and their prices fall. The second risk factor is the return on a long-short portfolio that combines borrowing at the 5-year swap rate and investing in higher risk BBB rated bonds. We refer to it as our *credit risk factor*. Positive exposure to credit risk corresponds to a long position in the portfolio and hence in BBB bonds. A bank with positive exposure to credit risk thus loses money when credit spreads widen so risky bond prices fall.

To define the credit risk factor as a portfolio, we must select appropriate portfolio weights. Our goal is to orthogonalize the factors, ensuring credit risk is isolated from interest-rate risk. We pick a weight of 2.5 on the BBB return and a weight of -1.5 on the swap-quality bond return that make the factors orthogonal in a subsample of *normal times*, defined as quarters with low volatility and positive correlation before 2022. In particular, we exclude 14 quarters of stress: 2002:Q2-Q4, 2011:Q3, the years 2008-9 and 2020:Q1-2. These dates are suggested by a regime-switching model, presented in Section 7.1 below. For now, our choice of weights just serves as a useful convention to describe risk.

Risk varies across subsamples in two key ways. First, before 2022, interest-rate risk served as insurance against credit risk during stress periods. The right panel of Figure 1 presents a scatter plot of factor realizations. In normal periods, shown as green dots, factor volatilities are relatively similar at 2.5% quarterly for interest-rate risk and 3.1% for credit risk, and are uncorrelated by construction. As a yardstick, we plot contour lines for a normal density with these parameters at 2, 4, and 8 times volatility. Times of stress before 2022 are marked by red numbers that indicate calendar years. These quarters exhibit much higher volatility. The 2008 financial crisis and the Covid recession are truly "off the chart," especially in credit risk. Moreover, before 2022, the factors are highly negatively correlated during stress periods.

Second, the 2022 banking crisis was unique as both risk factors declined together. We highlight 2022:Q1–2024:Q1 with purple dots connected by a southwest-starting line. The left panel flags 2022 as exceptional, with both spanning bond returns low, while the right panel shows the leveraged portfolio also experienced unusually low returns. In fact, these realizations are unusual compared both to normal times (green contours) and to typical stress periods (red contours that are based on a normal distribution with a pre-2022 stress-period covariance matrix). The insurance mechanism that once characterized stress periods was absent in 2022, as the interest-rate factor saw its worst realization in the entire sample.

To summarize, we have shown that the conditional distribution of bond returns *given the factors* is time-invariant, even though there is substantial time variation in the conditional volatilities and correlation of the factors themselves. The heteroskedasticity of individual bond returns is captured entirely by the heteroskedasticity in risk factors, while the risk exposures β^i of individual bonds in equation (1) do not depend on time t. When banks' risk exposures vary over time, we know that banks' portfolio weights on these bonds change, while individual bonds have constant exposures. At the same time, the result means that the interpretation of exposures depends on the state of the economy. For example, recessions have a larger likelihood of losses per dollar credit risk exposure. In this sense, our factors work much like credit ratings. We revisit this issue in Section 7.

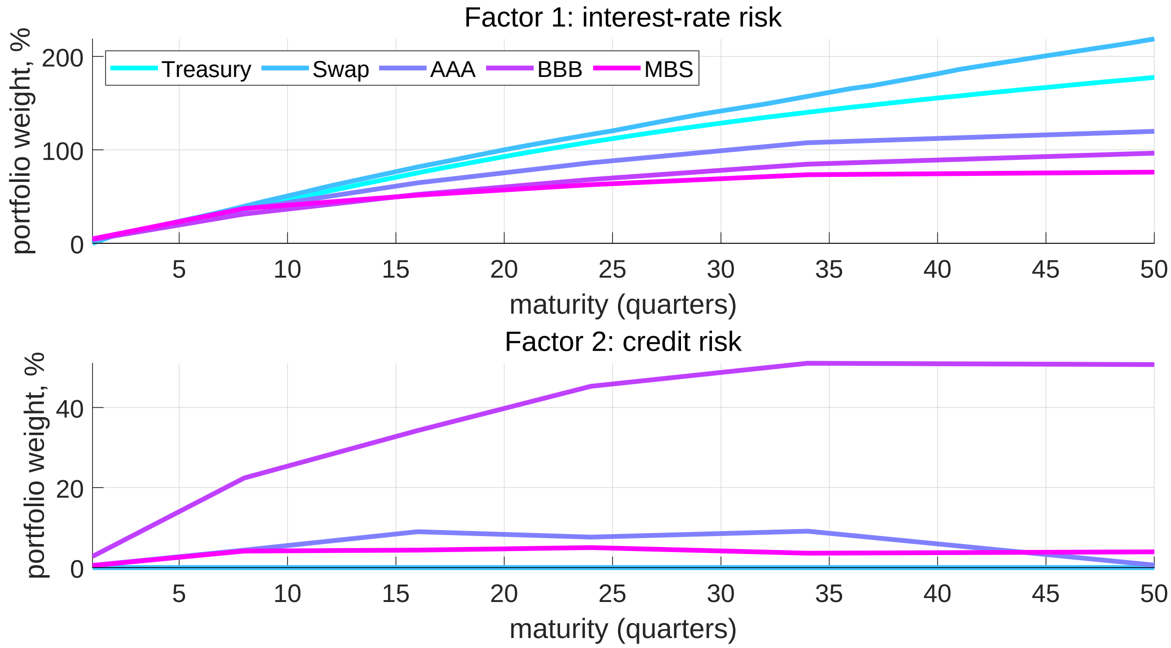
Factor loadings. The top and bottom panels of Figure 2 show replicating portfolio weights for many different bonds. For every dollar invested at some credit quality and some maturity, we can read off the implied interest rate (credit) risk exposure from the value taken in the top (bottom) panel by the curve for that credit quality at that maturity. For example, the light blue curve for swap-quality bonds in the top panel takes the value 100% at 20 quarters, as the 5-year swap-quality bond return matches the interest-rate risk factor. The light blue line in the bottom panel sits at zero since swap quality bonds are not exposed to credit risk.

More generally, longer-maturity bonds are more exposed to interest-rate risk than short-maturity bonds: all curves in the top panel are upward sloping. Moreover, interest-rate risk exposure declines with credit quality, holding maturity fixed. In other words, duration is not a sufficient statistic for interest-rate risk exposure in our framework. This is because lower-quality bonds are less correlated with the default-free bond return. At the same time, lower-quality bonds are more exposed to the credit-risk factor. In particular, the purple line for the BBB bond passes through 60% at 20 quarters. Since the weight on the swap-quality bond in the credit-risk factor portfolio is -1.5, a dollar invested in a BBB bond is the same as $1.5/2.5 = .6$ dollars in swap-quality bonds and $1/2.5 = .4$ dollars in the credit-risk factor. The purple line in the bottom panel thus passes through 40% at 20 quarters.

4 Replicating positions

This section provides an overview of the replication approach. For many positions, we observe the signs of risk exposure, including for loans, securities, long-term debt, and credit default swaps. Further details on those positions are in Appendix B and C. For interest-rate derivatives, we

Figure 2: Risk exposures of fixed-income instruments



Notes: Estimated factor loadings β_j^i from equation (1) for the interest-rate factor (top panel) and the credit-risk factor (bottom panel). Bond i is identified by maturity (measured along the horizontal axis) and credit quality (shown as different curves).

estimate the signs, with details in Appendix D.

Bank regulatory data. The balance-sheet data come from quarterly regulatory filings that banks operating in the United States provide to their regulatory supervisors. We focus on publicly traded domestic top-tier bank holding companies (BHCs), that is, BHCs not owned by another BHC or a foreign parent, that are chartered either as a commercial bank or as a holding company. Our sample is 1995:Q1-2024:Q1. For some positions, accounting information is only reported by commercial bank subsidiaries of a BHC; we thus rely on both bank-level and BHC-level reports. We also use information on mergers from the Federal Reserve Bank of Chicago.

Market value vs book value. The market value of a position is important for capturing its overall dollar exposures. For many positions, we observe banks' estimates of market value: *fair values*. For example, banks report fair values for all securities, including securities declared as "held-to-maturity" for which capital gains do not enter income. For most loans and long-term debt, banks report only *book values*, or face values.

Data on maturity and credit quality. Banks classify securities and loans by maturity and risk-weight buckets for capital requirements. Maturity reflects the time until repricing, which thus allows us to account for floating-rate loans. We map risk weights to credit ratings following regulatory guidelines. We use Call Report data to construct the joint distribution of credit quality and maturity for the fair values of securities. To compute the joint distribution for loan face values, we supplement the Call Report data with information from the Senior Loan Officer Opinion Survey on Lending Practices.

Replication of securities. To compute the factor portfolio that replicates a security position, we multiply the fair value of the position with the relevant exposures for that security from Figure 2. We then determine the cash position as a residual by matching the security's overall fair value.

Replication of loans. A bank's loan portfolio consists of numerous positions defined by their maturity and credit quality, as captured by the joint distribution of loan face values across ratings and maturities. To translate these positions into exposures, we note that a typical amortizing loan promises a stream of fixed payments. Each payment is the face value of a zero-coupon bond with the same credit quality as the loan position. Once we know the payments, we can use bond prices to determine fair values and compute exposures by applying the replication weights from Figure 2. As a by-product, this approach delivers an estimate of the market value for the loan portfolio.

To find the payment value associated with each loan position at issuance, we apply the standard annuity formula using the position's amortization period, interest rate, and face value as inputs. For fixed-rate loans, the amortization period corresponds to the contractual maturity; for floating-rate loans, it corresponds to the next repricing date. The loan's interest rate is given by its amortization period and its credit quality.

Using the annuity formula and the distribution of loan payment values, we infer the vintage distribution of loan face value positions in each period. We can identify newly issued loans and loan write-offs by comparing this inferred vintage distribution to the observed face value distribution. This, in turn, allows us to update the distribution of loan payment streams over time.

Replication of liabilities. We treat short-term debt as short-term bonds. This includes deposits with a contractual maturity of less than a quarter and trading liabilities, most of which are for short trading positions. For long-term debt, we follow a similar procedure as for loans. We construct payment streams and value these using bond prices.

Replication of credit derivatives. Banks report detailed information on their exposures through credit default swaps (CDS). In particular, we observe both notional values and marked-to-market fair values separately for protection bought and sold, as well as information on the maturity and credit quality of the underlying bonds. We view a CDS position that buys protection as a leveraged portfolio that converts a credit-risky bond into a default-free bond (for example, BBB to swap-quality bond). A position that sells protection does the opposite. Since the direction of the position is known, replication is straightforward.

To illustrate, for a position that buys protection, we construct a replicating portfolio that is short BBB and long swap-quality bonds such that (i) the face value of BBB bonds sold short matches the notional of the CDS position and (ii) the fair value of the position is matched. The unknown we solve for to achieve (ii) is the face-value of swap-quality bonds in the replicating portfolio. This approach assumes that nonzero fair value derives from a difference between the CDS spread locked in by the bank and the spread on a new CDS on the same bond, which would have zero fair value. The long position replicates the present value of locked-in spreads.

Replication of interest-rate derivatives. Interest-rate derivatives are highly collateralized contracts with payoffs that depend on swap-quality bond prices. We replicate them as portfolios of long bonds and cash that have zero value at inception but change value with bond prices afterward. Call reports contain the notional value N_t and the marked-to-market fair value F_t of the bank's overall interest-rate derivatives position, as well as information about its duration d_t.

Call report data do not tell us whether the bank is long or short interest-rate risk. In contrast to the case of CDS, where we know the direction of trading, forming a replicating portfolio is thus not immediate. We estimate the interest-rate risk exposure x_t, the value of swap-quality bonds in the replicating portfolio per dollar notional, from the available data on bank positions and bond-price changes. To see the basic idea, consider a bank with a derivatives portfolio that is always exactly equivalent to one unit of the 5-year spanning bond per unit notional and minus k dollars in cash. The exposure of this portfolio is $x_t = P_t$. From one quarter to the next, its fair value changes by exactly the bond-price change. An econometrician who observes both changes can infer the exposure x_t. It is positive (negative) if the fair value moves with (against) the bond price.

More generally, fair values also change as banks adjust their derivatives portfolios, for example by growing or shrinking notionals or duration. In Appendix D, we show that the joint distribution of fair value and the unobserved exposure x_{t+1} is

$$\begin{aligned} F_{t+1}N_{t+1} - F_t N_t &= \frac{\Delta P_{t+1}}{P_{t+1}} x_{t+1} N_{t+1} + N_t \varepsilon_{t+1}, \\ x_{t+1} &= \frac{d_{t+1}-1}{d_t - 1} x_t + \frac{d_{t+1}-1}{n-1}(\Delta F_{t+1} + u_{t+1}), \end{aligned} \tag{3}$$

where the random variables ε_{t+1} and u_{t+1} represent bank trades that do not alter notionals and duration.

The first equation in (3) relates the evolution of fair value to price changes and bank trading. The left-hand side is the fair-value change between dates t and $t+1$ per unit of notionals at $t+1$. The first term on the right-hand describes the effect of bond-price changes. In our simple example above, this is the only effect, so exposure can be read off the fair-value change. More generally, the bank might cancel part of the position that contributed (negatively or positively) to F_t, introducing a second term. The second equation captures that exposure declines mechanically as positions mature and duration declines (the first term) and moves with fair value due to gains on the position. In our simple example, the bank kept its portfolio constant with duration fixed at n, so $u_{t+1} = 0$. More generally, the bank might increase leverage by moving to 2 units of the bond and $-2k$ units of cash, a positive trade u_{t+1} that increases exposure.

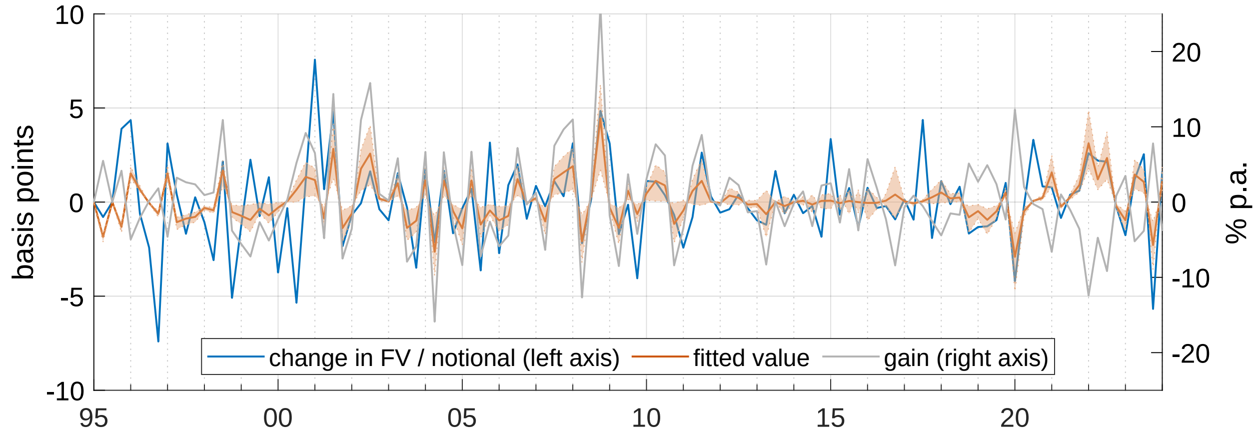
We estimate the system (3) assuming that the random variables ε_{t+1} and u_{t+1} have mean zero and are serially and mutually independent. The idea is to be agnostic about unobservable components in bank strategies and "let the data speak" as to how the banks trade. In particular, we do not enforce comovement between position cancellations and exposure changes beyond exogenous variation in duration and notionals. Nor do we impose mean reversion in bank trading beyond the mechanical effect in the second equation. The appendix details the argument and explains how to rewrite the system in state-space form for maximum-likelihood estimation.

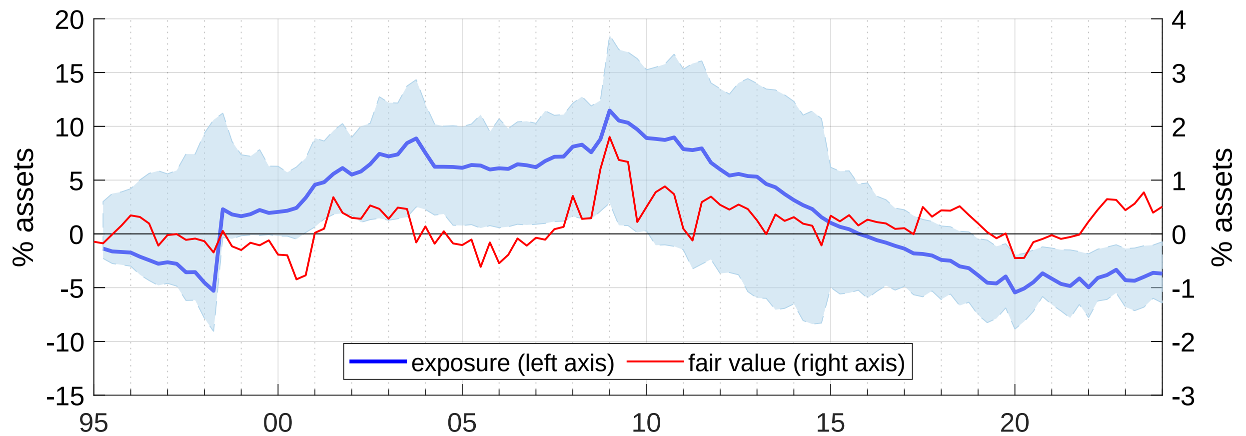
Figure 3 illustrates how the model uses comovement in fair value changes and price changes to infer the path of exposure for Bank of America. The blue line is the observable change in fair value per unit notionals, the left-hand side in the first equation of (3). It either moves with or against the price change $\Delta P_{t+1}/P_{t+1}$, shown as a light gray line. The estimated product, exposure x_{t+1} times price change, is shown in orange. For much of the sample, it resembles a smoothed version of the observable fair value changes. The bottom panel reports the estimated exposure. When the comovement between fair-value changes and price changes is positive, such as in the middle of the sample, the code infers $x_{t+1} > 0$. When the comovement is negative, such as at the beginning and end of the sample, it draws the opposite conclusion.

Overall, we infer three distinct phases in BofA's derivatives strategy. Before the 1998 merger with NationsBank, the portfolio resembled a relatively small pay-fixed position. After the merger, the bank built a substantial pay-floating position, especially in the runup to the financial crisis. As the increases in fair value (the red line) show, this resulted in substantial profits when the Fed lowered rates in the recessions of 2001 and 2008. The exposure was up to five times as large as fair value, revealing sizeable leverage. In recent years, the bank returned to a small pay-fixed position, which generated large profits when rates increased.

Portfolio income and accounting income. We now compare our portfolio income measure

Figure 3: Bank of America's for-trading swap portfolio





Notes: Top panel shows the change in fair value per unit of notionals $F_{t+1} - (N_t/N_{t+1})F_t$ (blue line), percentage price change in 5-year swap quality bond $\Delta P_{t+1}/P_{t+1}$ (gray), and price change multiplied by estimated exposure x_{t+1} (orange). Bottom panel shows the estimated exposure x_{t+1} (blue) and fair value F_{t+1} (red). Shaded areas in both panels are 95% confidence intervals.

derived from balance sheet positions and market returns to standard accounting income measures. We demonstrate a strong correlation between portfolio and accounting income at both the aggregate and individual bank levels, showing that our factor approach captures most bank income variation. Other risk factors, idiosyncratic bank-level volatility, or variation in various rents do not appear to contribute much to quarterly income variation. We also show that portfolio income is more volatile than accounting income, as one would expect, given that it includes unrealized capital gains that are missing from accounting measures.

Accounting income (AI) is the sum of net income and other comprehensive income (OCI) from the Call Reports.[9] We can decompose it as

$$\begin{aligned}\text{accounting income} = &\underbrace{\text{portfolio income} + \text{spread income} + \text{valuation discrepancy}}_{\text{accounting portfolio income} := \text{API}} \\ &- \text{loan loss provisions} + \text{net nonportfolio income},\end{aligned} \tag{4}$$

where portfolio income (PI) is the return on the replicating portfolio, as in equation (2).

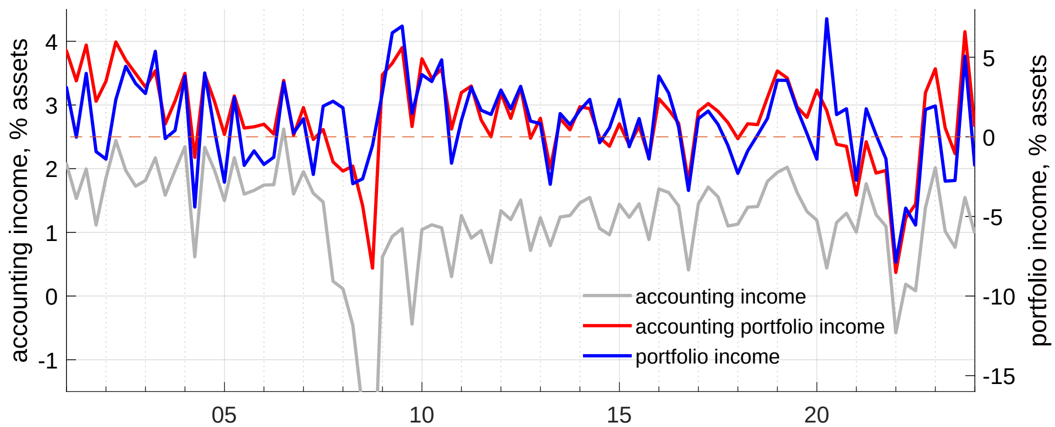
AI differs from PI by four components. First, *spread income* collects the pricing of the banks' services through interest-rate spreads, reported by the bank as part of net interest income. For example, spread income includes the spread that banks earn by paying deposit rates that are lower than other short-term interest rates. Second, a *valuation discrepancy* arises because accounting rules do not require banks to mark their entire portfolio to market. Instead, most loans, securities declared held-to-maturity, and long-term debt are all recorded at face value on the balance sheet so unrealized capital gains on those positions do not contribute to net income or OCI. In contrast, unrealized capital gains on positions held for trading or available-for-sale are included in net income and OCI, respectively. The sum of PI, spread income, and the valuation discrepancy provide an accounting measure of current gains and losses on the portfolio. We refer to it as "accounting portfolio income" (API).

Two other components of accounting income are only indirectly associated with current gains and losses on the portfolio. *Loan loss provisions* (LLPs) reflect precautionary measures taken to smooth income in the face of expected future shortfalls in loan repayment; they change as banks revise those expectations. We define *net nonportfolio income* (NNI) as net noninterest income less trading revenue. It primarily comprises fees and commissions (e.g., from investment banking and brokerage) minus employee compensation and fixed asset expenses. We can infer API from the directly observable AI, LLPs, and NNI, but not separately identify spread income and the valuation discrepancy from the Call Report data.

Figure 4 compares income measures. We focus here on the period since 2001:Q1 over which OCI is reported. The main takeaway is that API (in red) and PI (in blue) are very highly correlated. The correlation is 0.75 over the full sample since 2001 and 0.81 for the subsample since 2012. At the same time, PI has a volatility of 2.74% over the full sample, substantially higher than the volatility of API at 0.69%. This is not surprising in light of the valuation discrepancy described above; accounting rules are set up precisely to allow for income smoothing.

[9] OCI consists mostly of unrealized capital gains; it is a separate position in the Call Reports because it does not matter for regulatory capital requirements.

Figure 4: Alternative measures of income for U.S. banks



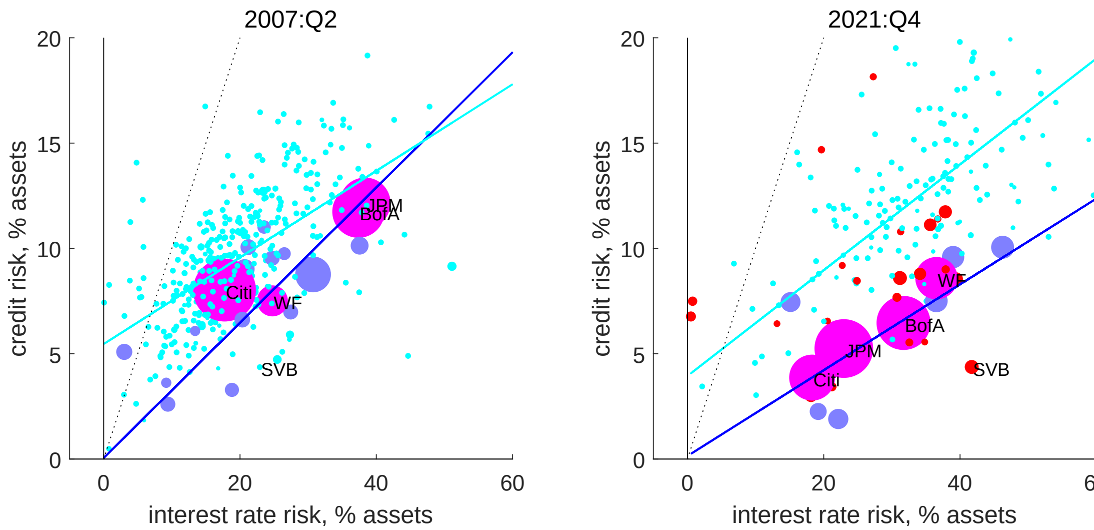
Notes: Income as in equation (4) in percent of assets for all public banks. Accounting income (gray, left axis), accounting portfolio income (red, left axis), portfolio income (blue, right axis).

We also show AI as a light gray line. It typically lies below PI because net nonportfolio income is negative, which largely reflects the cost of variable inputs such as labor. It also contains low frequency swings that lower the correlation with PI to 0.38 for the full sample. In particular, LLPs introduce a slow moving negative component in the wake of the financial crisis that is gradually reduced. In contrast, PI records large capital losses on loans right away when the financial crisis occurs, and then records large capital gains when spreads recede afterward. The correlation between AI and PI for the period since 2012 is 0.69.

The strong time series correlation between API and our concept of portfolio income holds not only on aggregate, but also at the individual bank level. We measure bank-level empirical correlation coefficients between API and PI for all banks for which we have at least 10 years (40 quarters) worth of data. The cross-sectional distribution of correlation coefficients has a median of 0.51, and an interquartile (IQ) range from 0.27 to 0.62. When we focus on the post-2012 sample, the median increases to 0.69, and the IQ range shifts to 0.54 and 0.77. Even the lower tail exhibits relatively strong comovement in recent data.

Correlation coefficients are generally larger for larger banks, and are especially high for the most important banks weighted by assets. When we restrict attention to banks with more than $10bn in assets on average, the median correlation coefficient over the full sample is 0.59 and the IQ range is between 0.45 and 0.65. In the sample after 2012, the median is 0.70, and the IQ range is [0.58, 0.78]. Among the 10 top bank holding companies by assets in 2024, the lowest correlation coefficients, for Bank of America and Capital One, are 57% and 65%, respectively, everyone else has correlation coefficients above 70%.

Figure 5: Risk exposures in the cross section of banks



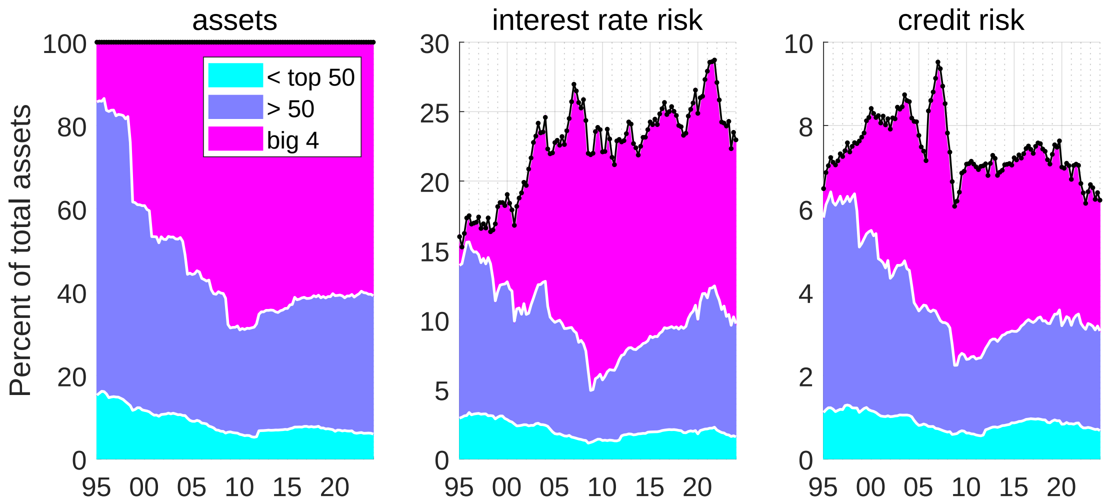
Notes: Scatter plots of individual banks' interest-rate risk and credit-risk exposures as a share of their assets in 2007:Q2 (left panel) and 2021:Q4 (right panel). Dot size increases linearly with a bank's share in total bank assets if that share is larger than 20bp. Colors in left panel: pink for big 4, purple if assets > \$50bn, light blue for all others; in right panel, red indicates assets between \$50bn and \$250bn. Asset-weighted regression lines are dark blue, equally-weighted are light blue.

We take away two messages. First, focusing on portfolio income volatility driven by just two risk factors effectively summarizes the income fluctuations banks experience. While bond market prices do not capture all risks, changes in spreads and valuation discrepancies seem insignificant for most banks' API movements, with a few exceptions. Moreover, idiosyncratic profitability changes—a major income risk for non-financial firms—play a minor role. Such changes would appear in NNI but even broad AI comoves strongly with PI for most banks. The second message is that the valuation of unrealized capital gains is a large component of bank income volatility, missing from accounting net-income.

5 Exposures across banks and over time

This section provides a first look at risk exposure numbers and presents our proposal for stress testing. Section 5.1 documents trends in overall exposure by group of bank. Section 5.2 describes through which instruments banks build exposure. Section 5.3 shows how to use exposures to project income forward.

Figure 6: Consolidation of assets and risk exposures



Notes: Assets (left panel), interest-rate risk exposures (middle panel), and credit-risk exposures (right panel) as a share of total banking sector assets with subgroups indicated by colors.

5.1 Risk and bank heterogeneity

Figure 5 shows the cross section of risk exposures for 2007:Q2 (left panel) and 2021:Q4 (right panel), the two quarters preceding the two major banking crises in our sample. It highlights three stylized facts that are true throughout our sample. First, *interest-rate risk positions are much larger than credit-risk positions*. Second, *there is a lot of heterogeneity in risk exposures across banks*, even within size classes, indicated by different colors. Finally, *interest-rate and credit-risk exposures are strongly positively correlated*. Both asset-weighted and equally-weighted regression lines (dark and light blue, respectively) are upward-sloping.

Small versus large banks. Small banks have more credit risk than large banks. In both panels, most small banks (light blue dots) sit north of the pink labeled big 4 (JP Morgan Chase, Bank of America, Citi and WellsFargo). In 2007, the big 4 had more interest-rate risk, east of most small banks. However, between 2007 and 2021, small banks increased both exposures while large banks reduced credit-risk exposures. As a result, many small banks surpassed the big 4 in 2021 in both risk dimensions. In 2021, mid-sized banks (purple or red) appear more similar to the largest banks than in 2007, having shifted away from credit risk and toward interest-rate risk. In the right panel, we highlight in red the banks between \$50bn and \$250bn in assets that received less regulatory scrutiny since the 2018 Dodd-Frank rollback, including Silicon Valley Bank. Many of them are far east.

Concentration and consolidation in US banking. The distribution of assets is highly skewed.

The big 4 banks account for about one-half of all assets. Among mid-sized banks, there are several very large dots, indicating concentration within that group as well. Finally there is a large fringe of much smaller banks. While the number of small banks is much lower now than in 2007, their asset weight is about the same. Figure 6 illustrates the consolidation process by showing their contributions to total assets, total interest-rate risk, and total credit-risk positions. Until the financial crisis, the big 4 grew rapidly, mostly through acquisitions of other relatively large banks, visible as steps in the shares of the big 4 and the top 5-50.[10] After the financial crisis, group weights have been roughly constant.

The consolidation process coincided with a large increase in overall interest-rate risk and a smaller but significant increase in credit risk, both concentrated in the top banks. After the financial crisis, larger banks maintained roughly stable interest-rate risk exposure until 2020 while reducing their credit risk. In contrast, we note a build of interest-rate and credit risk exposure in small and especially mid-sized banks since 2008, despite their unchanged aggregate asset shares. Aggregate credit risk has recently hit a historical low, driven primarily by declines at large banks.

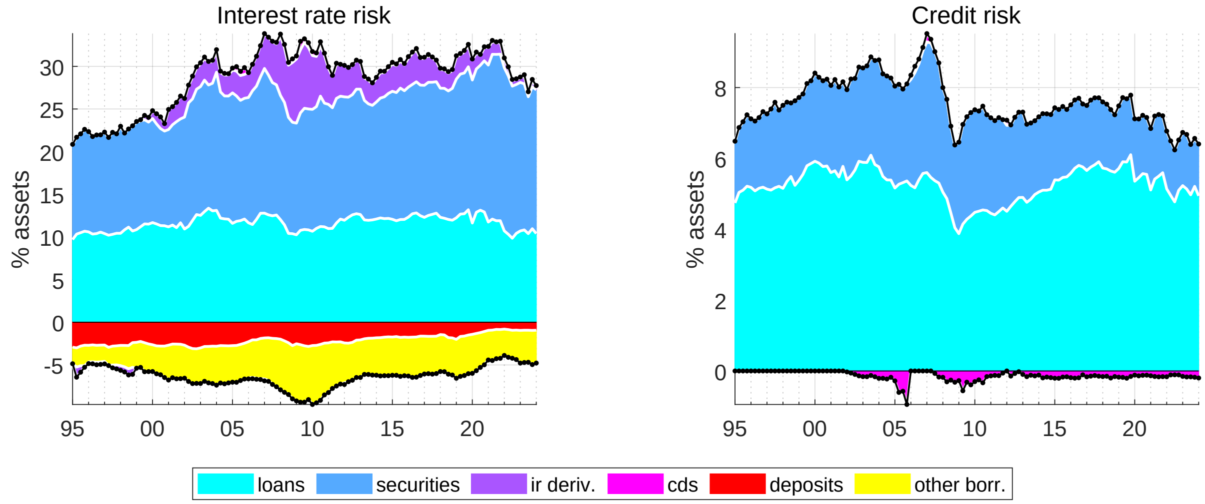
5.2 Sources of exposure

How do banks build risk exposures? Figure 7 shows how the contributions of key balance-sheet positions to interest-rate risk (left panel) and credit risk (right panel) evolved over time. For interest-rate risk, there is a small but nonnegligible negative contribution from long-term liabilities, which we break up into (red) term deposits and (yellow) other borrowing, plotted as negative numbers. Similarly, for credit risk, there is a small negative position from net purchases of protection using credit default swaps. For comparison, total risk exposures in the middle panel of Figure 6 are net positions, defined as differences between all positive and negative positions in the left panel of Figure 7. We note that negative exposures from long-term liabilities peaked around the financial crisis and have recently become less important.

Loans and securities. Banks build most risk exposures through loans and securities. The contribution from loans relative to assets has been remarkably stable over time. Loans tend to have shorter maturity and lower credit quality than securities, so they are relatively more important in contributing to credit-risk exposures. Securities, in contrast, are relatively more important for interest-rate risk exposure. In particular, sharp runups of interest-rate risk exposure ahead of both

[10] Our time series exercises use a dynamic sort of banks by rank, whereas the cross-sectional plots use Dodd-Frank size cutoffs. However, the stylized facts we emphasize are very similar when the group ranked 5-50 is identified with mid-sized banks with assets larger than $50bn and below the big 4. This motivates our use of the same color scheme for the two types of figures.

Figure 7: Contribution of balance sheet positions to risk exposures



Notes: Contributions to interest-risk exposure (left panel) and credit-risk exposure (right panel) by balance sheet item for all public banks. Contributions of non-derivative positions on the asset (liability) side are recorded as positive (negative) numbers. Contributions of derivative positions are recorded according to the sign of the net position.

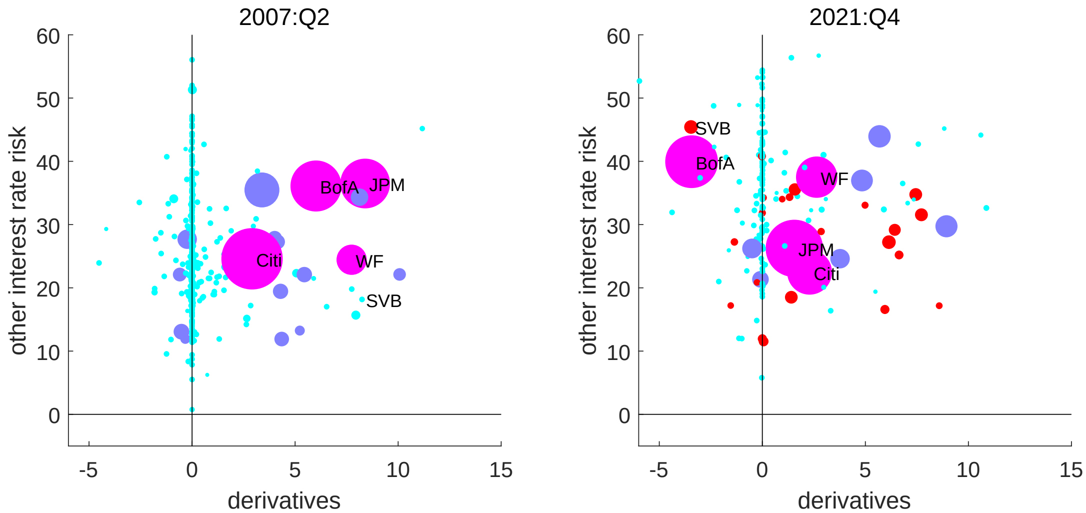
the financial crisis and the recent 2022 banking troubles were due to increases in securities. Figure 7 highlights that exposures to our two risk factors are highly correlated, especially at business cycle frequencies, such as during the 2007 recession.

Derivatives. Throughout the sample, the interest-rate derivatives position of the aggregate banking system typically *increases* its interest-rate risk exposure. On net, banks hold pay-floating swaps that do well when rates fall, like long bond positions. Banks do not use interest-rate derivatives to hedge their securities or loan positions, representing long bond positions. In particular, a significant buildup of interest-rate risk occurred at the sample's beginning after the Glass-Steagall Act was abolished.[11]

In contrast, the contribution of net positions in credit-default swaps typically *reduces* credit risk, although the effect is quantitatively small. Throughout much of the sample, the banking system as a whole is a net buyer of protection, replicated by a negative position in credit risk. The net position contains negligible interest-rate risk, as one would expect if banks mostly transform defaultable bonds into default-free bonds with the same duration. Interestingly, the net position flips sign at the height of the financial crisis, when banks temporarily became net sellers of protection, visible as a small positive contribution to credit risk in the right panel.

[11]Once commercial banks could freely merge with investment banks, mergers led to large universal banks such as JP Morgan Chase, established in 2001.

Figure 8: Interest-rate risk exposure from derivatives and other business



Notes: Scatter plots of interest-rate risk exposures due to interest-rate derivatives (horizontal axis) and other business (vertical axis) in 2007:Q2 (left panel) and 2021:Q4 (right panel) relative total assets. Dot size increases linearly with a bank's share in total bank assets if that share is larger than 20bp. Colors: pink for big 4, purple if assets > \$50bn, light blue for all others; in right panel, red indicates assets between \$50bn and \$250bn.

Interest rate derivatives in the cross section. Figure 8 takes a closer look at banks' interest-rate derivatives. Panels for 2007:Q2 (left) and 2021:Q4 (right) show interest-rate risk exposure through derivatives along the horizontal axis and all other positions along the vertical axis. Banks that hedge other asset positions with derivatives are in the top-left quadrant. While many smaller banks hedge with derivatives, those positions tend to be small relative to assets. Most large banks in both periods instead use derivatives to add to their positive exposures from other positions.[12]

The two panels also show how participation in derivatives markets has changed towards more participation by smaller banks that build significant positions. To illustrate, in 2007, 52% of banks had some notionals in interest rate derivatives, but only 11% had notionals in excess of 10% of assets. Many positions at that time were small and declared not for trading. In 2021, in contrast, 72% of banks participated and 40% had notionals of more than 10%. Many more banks have assembled sizeable for-trading positions in recent years. We see large exposures, especially at mid-sized banks below the big 4 (in purple) and banks that recently moved below the SIFI threshold for Dodd-Frank stress testing (in red).

[12]The exception is BofA in 2021:Q4, as discussed in Section 4. SVB exited its interest-rate hedges in early 2022 according to page 3 of https://www.federalreserve.gov/publications/files/svb-review-20230428.pdf.

5.3 Stress testing portfolio income

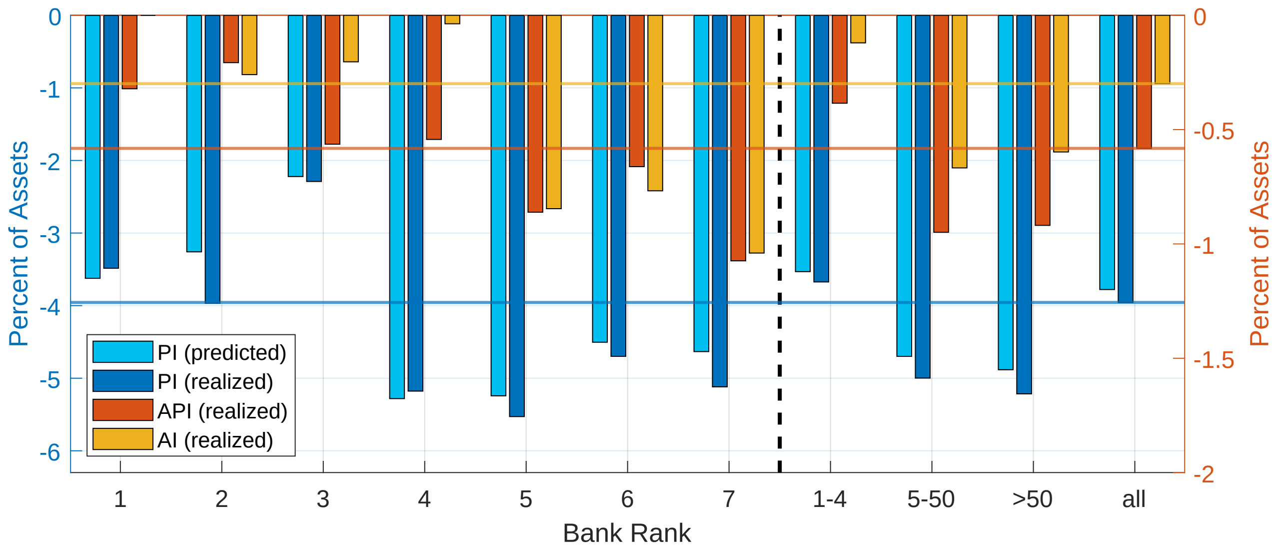
Stress tests are designed to assess the effect of large shocks on bank income and, thereby, bank equity. The typical approach is to describe one or more detailed scenarios for the path of macroeconomic indicators as well as asset prices over some period, say two years, and ask banks to project forward components of income for this period. An advantage of this approach is that projections of accounting income feed into projections of current regulatory measures of bank health, such as capital ratios. Moreover, it simulates, for each scenario, the use of accounting rules to smooth income components, which are at the discretion of each bank. As a result, many calculations go into each scenario.

An alternative to stress testing. We now show that our framework offers a simple approach to stress testing based on projections of portfolio income. Suppose we fix risk positions x_t at some date, define a scenario by a path of risk factors $f_{t+1}, f_{t+2}, \ldots$ over some period, and compute the resulting path of portfolio income based on equation (2). This straightforward calculation can be done very quickly for many alternative scenarios. To illustrate our approach, we mimic the last stress test before the 2022 banking crisis, which asked banks in December 2020 to forecast income for 9 quarters through the end of 2023:Q1.

Medium-term projections of portfolio income. We first establish that 9-quarter projections of portfolio income with constant exposure provide an accurate assessment of the *realized* return scenario. We thus compute, for every bank, a forecast error as the difference between actual portfolio income and the projection using *realized* returns over the stress horizon. Annualized portfolio income over the stress test horizon had a mean of -2.3%, a median of -2.5% and an interdecile range from -3.2% to -1.4%. The absolute forecast error, in contrast, is almost an order of magnitude smaller, with a mean of 36bp, a median of 30bp, and an interdecile range from 8bp to 65bp. Moreover, the cross-sectional correlation of predicted and actual portfolio income is 84%.

In particular, our approach works well for the largest banks. The light and dark blue bars in Figure 9 show predicted and actual annualized changes in portfolio income relative to the previous 9 quarters for the top 7 banks by assets at the end of 2020: JPMorganChase, Bank of America, Citicorp, Wells Fargo, USBancorp, Truist, and PNC. Together, those banks account for 58% of total assets. The light blue bars for predicted income and the dark blue bars for actual income are close together. To the right of the dashed vertical line, we further display predicted and actual portfolio income changes by size groups and for all banks. Overall, we conclude that using the realized return scenario together with the initial risk exposure delivers a remarkably accurate prediction of the actual income trajectory.

Figure 9: Changes in income over stress test period by bank size



Notes: Bars are changes in income for stress test period 2021:Q1-2023:Q1 relative to previous 9 quarters, in percent of assets per year for top 7 banks by assets as well as groups defined by asset rank. Portfolio income (blue bars) measured on left axis, accounting income (orange bars) on right axis. Horizontal lines indicate average change in income for all public banks (value-weighted).

Intuitively, our simple approach works better when the variation in income comes more from price changes and less from banks' changes in exposures, which we do not take into account. This is why our focus on a stress period like 2022-3, where banks might be more prone to rebalance, is particularly interesting as a check. For more quiet episodes, we generally find that the forecast errors are even smaller. As another example, consider projections starting in 2014:Q4 over 9 quarters until 2017:Q1. Annualized portfolio income over this horizon had a mean and median of 1.1% as well as an interdecile range from .6% to 1.5%. The absolute forecast error has a mean of 10bp, a median of 7bp, and an interdecile range from 1bp to 21bp, and the cross-sectional correlation of predicted and actual portfolio income is 92%.

Predicting relative vulnerability of banks. Figure 9 further illustrates that our approach would have correctly anticipated the vulnerability of small and mid-sized banks to joint increases in interest rates and spreads, the hallmark of the realized factor return path. Indeed, the blue horizontal line marks the loss for all banks, the rightmost blue bar. Among the top 7, actual losses at banks 1-3 were below this average, whereas banks 4-7 did worse. Among the groups, the big 4 outperformed the average, while small and mid-sized banks did worse. The light blue bars for predicted income also reflect these patterns. If a regulator had considered this scenario at the end of 2020, the warning signs would have been clear.

Table 1: Projections of income/assets, 2020:Q4-2023:Q1

Bank ranks, Q4 2020	1	2	3	4	5	6	7	1-4	5-50	>50	all
Projections under Fed's 2020 stress test scenario, % assets											
Fed stress test (AI)	-0.2	-0.4	-0.2	-0.6	0.1	-0.3	-0.3				
this paper (PI)	-1.2	-1.1	-0.8	-1.8	-1.9	-1.9	-1.5	-1.2	-1.8	-2.1	-1.4
Realized income measures , % assets											
accounting (AI)	1.3	0.9	0.8	0.8	0.7	0.4	0.4	1.0	0.9	1.0	1.0
portfolio (PI)	-1.7	-2.1	-1.1	-2.4	-2.9	-2.7	-2.8	-1.8	-2.6	-2.5	-2.0

Notes: Annualized measures of income 2020:Q4-2023:Q1 as percent of assets in 2020:Q4. Columns contain top 7 public banks by assets as of 2020:Q4, and asset-weighted averages for 3 groups of banks ordered by rank and all public banks. Top panel: Fed projection for top 7 banks of AI under severely adverse scenario of 2020 stress test, portfolio income = sum of factor returns under severely adverse scenario multiplied by 2020:Q4 exposures. Bottom panel: portfolio income and accounting income as defined in equation (4).

Portfolio income vs accounting income. Importantly, forecasting portfolio income would also have been valuable for a regulator who cares about accounting income, the measure projected in official stress tests. This is illustrated by the dark and light orange bars in Figure 9, which show the annualized change in accounting portfolio income (API) and accounting income (AI), respectively, as defined in Section 4. We focus on changes relative to the previous 9 quarters to remove bank or bank-group fixed effects. We thus see how unusual the crisis was for each bank or bank group.

Comparing the blue and orange bars shows that the ranking of losses is broadly similar across all income measures: smaller banks suffered more than the average, again indicated by horizontal lines of the same color, and larger banks suffered less. Size matters both across groups (big 4 vs 5-50 and >50 banks) but also within the top 7. For example, the more traditional banks ranked 5-7 performed worse than the big 4. An interesting special case is Wells Fargo (bank 4) which achieved relatively high accounting income even though its portfolio income was low. Overall, we conclude that simply projecting portfolio income would have contained relevant information for accounting income. This is not entirely surprising given the close correlation of income measures we have documented in Section 4. Here, we learn that the correlation is strong enough that our projections can flag vulnerable banks in the sense of expected accounting income losses in the cross-section.

Stress test projection vs predicted portfolio income. In Table 1, we compare our approach to the actual 2020 stress test. The first line in the top panel reports publicly available projections of accounting income for the top 7 banks under the Fed's "severely adverse" scenario. This scenario envisioned a typical recession in early 2021, with wider credit spreads and lower Treasury yields, and a subsequent gradual recovery. The scenario description contains an entire path for the 10-year BBB and 10-year Treasury yields that we use to back out a stress-scenario path of factor returns. The second line reports projections of portfolio income that we would have made in 2020 under the severely adverse scenario. Realized returns, which include the 2022 crisis, differ from this scenario because the Fed tightened to fight inflation, leading to sharply higher Treasury yields.[13]

The Fed's projections were similar for most of the top 7 banks: accounting incomes ranged between $-.2\%$ and $.1\%$, with the exception of Wells Fargo as the most vulnerable bank at $-.6\%$. The severe adverse scenario was pessimistic compared to the realized outcome, shown in the first line of the bottom panel: since there was no major recession during these 9 quarters, actual incomes remained positive. Our portfolio income projections would have been more pessimistic than the Fed's accounting income projections, as one would expect, since we take into account all unrealized capital gains. At the same time, realized portfolio incomes came in even worse in the bottom panel of Table 1 because the severe adverse scenario did not anticipate the Fed's rate hike. As we have seen in Figure 9, our approach would have also closely matched the realized outcome under this realized scenario.

Perhaps the most interesting finding is that our approach would have flagged the vulnerability of the smaller banks *even under the original stress test scenario.* Indeed, our projection of portfolio income in Table 1 ranks banks 4-7 as clearly worse than banks 1-3. This is in contrast to the Fed's approach that saw similar losses at all top 7 banks. Moreover, since we can easily apply our approach for all banks, we also report results for bank groups. We find that smaller and mid-sized banks overall would have been projected to lose more than the big 4. Again, we emphasize that the variables being forecasted here are not the same, which explains part of the difference in results. Our framework emphasizes capital gains, which play a small role in stress tests. In fact, stress tests projected only small OCI losses for all banks.

We conclude that our framework provides a simple way to do many stress tests with multiple scenarios without relying on banks' own apparatus of projecting income according to accounting rules. When we feed in the correct scenario, our framework produces an accurate projection of portfolio income. Even for alternative scenarios, such as the one considered by regulators in the December 2020 stress test, it flagged the vulnerability of smaller banks, which came as a surprise relative to the results from the actual stress test. Finally, since our approach is cheap to implement,

[13] The Jan 8, 2025 article "Stress Testing 101" by the Bank Policy Institute discusses the fact that *no crisis is alike*, which poses a significant challenge for stress testing, https://bpi.com/stress-testing-101/.

it can be used to easily gauge vulnerability for the entire distribution of banks.

6 Trading dynamics and returns

This section studies cyclical patterns of risk taking. Figure 7 already shows that risk exposure moves around. A natural hypothesis is that banks "time the market", taking on more risk when expected excess returns are higher. In this case, we should be able to predict excess returns on our risk factors using bank positions.

Banks mistime the market. Table 2 shows results from regressions of the excess return on our interest-rate risk factor on the interest-rate risk position. The dependent variable is the one-year holding period return on the 5-year swap-quality bond less the one-year swap rate. We regress it on a constant and the ratio of interest-rate risk (credit risk) to assets at the beginning of the holding period. We report standardized regression coefficients and t-statistics based on Hansen-Hodrick standard errors with 4 lags for the full quarterly sample from 1995 to 2023 and a subsample that starts in 2012, which omits the financial crisis and covers the period of mostly low rates. We run the regressions for two groups of banks: all public banks and small banks outside the top 50.

We find that larger interest-rate risk positions do not predict higher returns on the interest-rate risk factor. All point estimates for interest-rate risk are negative. When we focus on traditional bank business, we find exactly the opposite: higher exposure predicts *lower* returns. This result is statistically significant for small banks throughout and for large banks if we either focus on the recent sample where the use of derivatives is small or the full sample when we leave out exposure through derivatives. This finding underscores our general theme that large and small banks have become more similar after the financial crisis. In the recent sample, the result is very strong, with R^2s unusually high for a predictability regression.

The results are economically significant. For small banks over the full sample, a one-standard deviation increase in interest-rate risk exposure is a 3.6% increase in exposure relative to assets. From Table 2, this increase predicts a 2.2pp lower excess return over the following year. The average loss on the extra risk position alone is therefore $3.6 \times 2.2\% = 7.9$bp of total assets, or 5.9% of average pre-tax income. Since the information that led banks to load up on interest-rate risk could have been used to time the market in the other direction, the overall loss is even larger. For the subsample after 2012, the standardized coefficient is much larger, but positions also move less relative to assets. Implied losses on the increased positions are similar for small banks at 6% of average income and 3% of income for large banks. We conclude that the result cannot be

Table 2: Predicting excess returns on long swap bond with exposures

	all public banks					small (>50)			
	1995-2024			2012-2024		1995-2024		2012-2024	
			no deriv						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
int. rate risk	-1.2	-1.2	-2.6	-5.9	-3.1	-2.2	-4.3	-4.3	-3.8
(t-statistic)	(-1.0)	(-1.1)	(-3.3)	(-4.3)	(-7.1)	(-2.4)	(-3.7)	(-5.7)	(-4.6)
credit risk		1.3			1.5		2.4		1.4
(t-statistic)		(1.8)			(1.9)		(2.1)		(1.3)
Observations	113	113	113	45	45	113	113	45	45
Adj. R^2	0.05	0.10	0.24	0.42	0.52	0.18	0.24	0.42	0.47

Notes: Regressions of 4-quarter ahead excess return on 5-year swap-quality bond over 1-year swap rate, on asset-weighted average interest-rate and credit-risk exposures for different groups of banks measured in percent of assets. T-statistics based on Hansen-Hodrick standard errors with 4 lags in parentheses. Column (3) considers exposures of all public banks in their non-derivatives portfolios.

chalked up to an insignificant oversight. Below, we explore the economic rationale behind banks' strategy.

Adding the credit-risk factor to the predictability regression does not change the basic result. In all specifications, the point estimate on credit risk is positive. Moreover, adding credit risk as a predictor in the full sample regressions increases the significance of the coefficient on interest-rate risk. Intuitively, in the early sample before the financial crisis, adding credit risk leads to a cleaner estimate of the effect of interest-rate risk. In fact, the regression for small banks shows a statistically significant coefficient (of -2.2 with a t-statistic of -2.4) for interest-rate risk even over the full sample alone.

Mistiming and asset trades. The predictability regression relates high exposure at a point in time to low subsequent excess returns. It does not speak to *why* exposure was high. One possibility is that bank positions are illiquid and exposures sometimes rise because of temporary price increases. When prices subsequently revert to the mean, the high exposure is followed by low excess returns. Alternatively, it could be that banks actively change their portfolios to load up on risk before low excess returns. Our framework can distinguish these alternatives, because we can decompose the change in exposure into effects due to either price changes or trading behavior by the bank.

Formally, we denote assets at date t by a_t and write the change in exposure to factor j relative to assets over a horizon of h periods as the sum of three parts:

$$\frac{x_{t+h,j} - x_{t,j}}{a_t} = \frac{x_{t,j}}{a_t} \sum_{\tau=1}^{h} f_{t+\tau,j} + \left\{ \frac{x_{t+h,j}}{a_{t+h}} - \frac{x_{t,j}}{a_t} \left(1 + \sum_{\tau=1}^{h} f_{t+\tau,j} \right) \right\} + \frac{a_{t+h} - a_t}{a_t} \frac{x_{t+h}}{a_{t+h}}$$

The first component is the *capital gain:* the old position $x_{t,j}$ multiplied by the factor return $f_{t+\tau,j}$. It is zero if the factor return is exactly zero, so there are no gains or losses on the position. If the bank position is completely illiquid, then the capital gain explains the entire change in exposure.

The remaining two terms reflect changes in exposure due to bank trading activity. Here we further distinguish changes in the portfolio weight (exposure over assets) from expansion of the bank. The second component, in braces, is the change in the portfolio weight on factor j that is not accounted for by capital gains. We refer to it as the *trade* component: if it is positive, say, then the bank increases its weight on factor j. It is zero if the bank passively lets its weight change via the capital gain. The final term is the change in position that occurs if the bank adds additional assets at its new portfolio weight. We refer to it as the *growth* component. A bank may have zero trade but positive growth when it lets its weight passively adjust but then replicates itself at this new weight.[14]

Figure 10 plots the three terms of the decomposition for all public banks with j the interest-rate risk factor and a horizon h of four quarters. At every date, the one-year change in the position relative to assets is the sum of the three colored areas, which can be positive or negative. We also plot the 5-year swap rate as a green solid line. Two patterns emerge clearly. First, bank trading activity (purple plus pink) is quantitatively more important than capital gains (light blue). This is inconsistent with an illiquidity explanation for mistiming. Second, both capital gains and trading activity are systematically related to the level of interest rates. In particular, bursts of trade and growth occur when interest rates have fallen, in 1998, 2002, 2012, 2016 or 2020. Moreover, capital gains are negative in the aftermath of these periods when rates rise again. The period around the financial crisis is an exception: banks built up risk during the housing boom as rates rose and shed it during the crisis when they fell.

The fact that banks actively seek out riskier positions when interest rates are low suggests an explanation for mistiming based on their business model as liquidity providers. It is well known that when the level of interest rates falls, deposit spreads compress and deposits flow into banks

[14]We note that when a positive position, say, is completely illiquid, then a positive return implies positive growth of assets but also lowers the portfolio weight so the two effects cancel and the change in exposure is indeed only the capital gain.

as their opportunity cost to bank customers declines. Figure 10 shows that banks respond by purchasing relatively more long-duration assets to back deposits: they shift their portfolio weight towards more interest-rate exposure (the purple regions) and expand the bank at a higher portfolio weight (the pink regions). Such a strategy can be optimal if the objective is to smooth the net interest margin, as encouraged by regulators. Since deposit rates typically rise less than one-for-one with interest rates, buying longer-duration assets matches the rate sensitivity of the asset and liability side of the balance sheet.

The comovement of deposits and risk exposures supports our interpretation of mistiming due to liquidity provision. In Appendix F.1, we show that bursts of risk taking, especially after 2012, are indeed associated with bursts of deposit growth. After 2012, the correlation between changes in deposits and interest-rate risk exposure is 75%. For smaller banks, for which mistiming is stronger throughout the sample, the correlation is high (above 85%) throughout the sample as well. Comovement is weaker for larger banks before 2012, in part because of growth through consolidation and because large banks relied more on wholesale funding for the risk buildup before the financial crisis. For the period after 2012, large and small banks look quite similar in that deposit flows drive the scale of operations, and income smoothing can explain why risk increases even when expected excess returns are low.

We note that our measure of portfolio interest rate exposure is conceptually different the *income gap*, that is, the difference between assets and liabilities that reprice or mature within one year. The income gap proxies the change in a bank's net interest margin (NIM) when the short interest rate rises (see OCC 2020 for the use of NIM in regulation). Since one way to increase the income gap is to invest in short-duration (and hence short-rate-sensitive) assets, a high income gap may indicate low interest-rate exposure of the bank portfolio. However, it may alternatively reflect a large share of funding through rate-insensitive deposits.[15] Interestingly, when interest-rate risk exposures increase with deposit inflows, as we document, both high interest-rate risk exposures and high income gaps can predict low excess returns on long bonds (see Haddad and Sraer 2020 for predictability results using income gaps).

[15] As a stark example, consider a bank that holds only perpetuities with constant coupon payments and funds itself with zero-interest deposits and equity. This bank has a constant NIM, while its portfolio income fluctuates with the market value of the perpetuities, taking into account losses that would realize if the depositors were to leave. Moreover, the bank has an income gap of zero since neither perpetuities nor zero interest deposits are rate sensitive. If it were funded with 3-month repos instead, its income gap would be lower at minus the debt/asset ratio. However, the interest-rate risk exposure of the bank's portfolio is the same in both cases: the one-quarter-ahead portfolio income risk comes only from capital gains on the perpetuity. The difference in funding cost only adds a constant spread component to portfolio income.

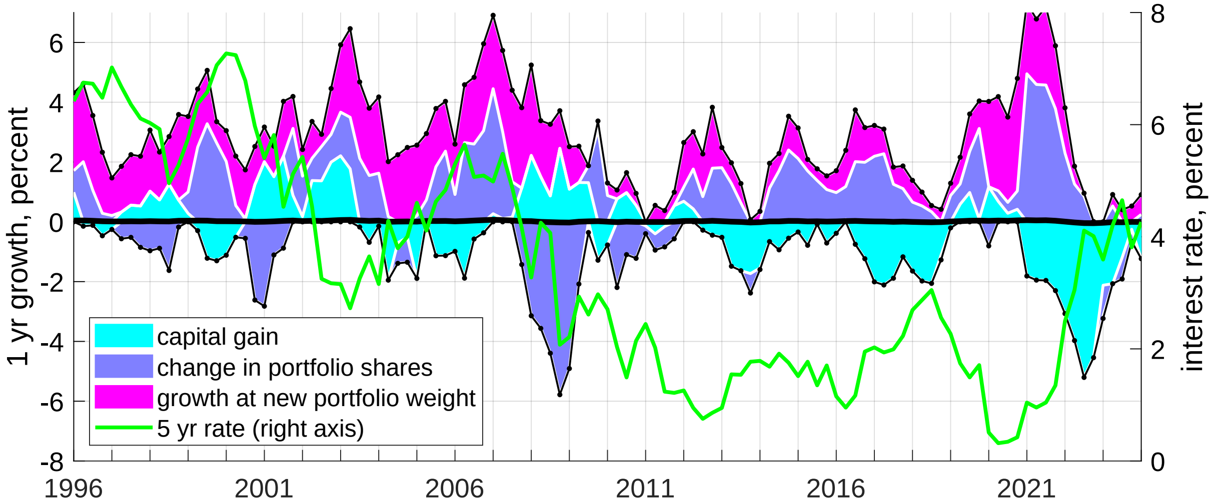


Figure 10: Contributions of balance sheet positions to growth in risk exposure

7 Alternative risk measures

Our approach summarizes bank risk-taking at any point in time by risk exposures and assesses bank vulnerability to shocks by thinking through scenarios for factor realizations. We have used statistical analysis only to relate bond returns to factors but have not modeled the dynamics of factor returns themselves or the dynamics of bank positions or income. This section discusses two related approaches that rely relatively more on statistical analysis. As a point of comparison, we focus on the most recent banking crisis in 2022-3.

We first ask whether a *single* number can summarize bank risk by modeling the distribution of factors. Section 7.1 shows this goal is difficult to achieve because the conditional volatilities and correlation of the factors change over time. In particular, the conditional distribution before 2022 is well described by a regime-switching model, where factors become more volatile and negatively correlated in recessions. Even relative to that model, however, the 2022-3 crisis is special in that both factors came in very low. We conclude that scenario analysis is a better route.

Risk exposures are the key input for scenario analysis. Section 7.2 asks whether these exposures can be computed by simply running regressions of bank performance measures on factors. This approach is common in the literature, which often focuses on banks' stock return "betas". While using regressions to measure risk exposures is attractive due to its simplicity, it works only if exposures move slowly over time. We show that, in 2021:Q4, scenario analysis with regression-based exposure measures would have led to large errors for both income and stock returns. For stock returns in particular, this is because the correlation of bank franchise value with factors changes along with the broader bond-stock correlation.

7.1 The time varying distribution of risk factors

Figure 1 shows that our spanning bond returns move together outside the two major recessions and a few additional episodes of financial stress, where they move in opposite directions. This pattern suggests a regime-switching model with two regimes, normal times and times of stress. We specify dynamics for demeaned spanning bond returns as

$$r_{t+1} = \sigma(z_t)\,\varepsilon_{t+1}, \tag{5}$$

where the regime z_t is a two-state Markov chain and the innovations ε_{t+1} are iid standard normal. The matrix $\sigma(z)\,\sigma(z)^\top$ is the one-quarter ahead covariance matrix of the factors in regime z.

Table 3 presents results from a maximum-likelihood estimation over the sample 1995-2021. We leave out the 2022-3 episode here since it is short and unique within our sample. Before 2022, higher volatility was associated with negative comovement of bond prices with and without credit risk. The estimation thus selects a short-lived stress regime with high volatilities for both returns and mild negative (and actually statistically insignificant) correlation and a longer-lived normal regime with low volatilities and strong positive correlation. The stress regime picks up periods when spreads rise and monetary policy responds by easing.

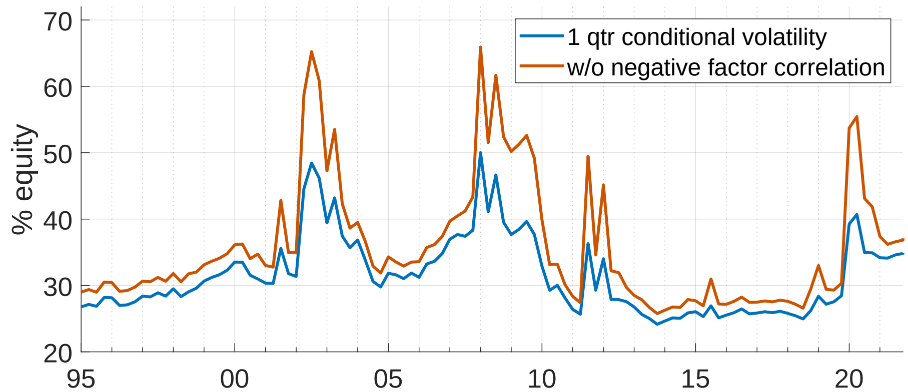
The estimates for bond-return dynamics in Table 3 imply time-varying conditional moments for our risk factors. The volatility of the interest-rate risk factor, identified with the swap-quality

Table 3: Regime-switching model for spanning bond returns

	transition matrix			volatilities & correlation			
	normal	stress	returns	normal		stress	
normal	0.9 (0.0)	0.1 (-0.0)	swap	10.7 (0.7)	0.8 (0.0)	16.6 (2.9)	-0.2 (0.2)
stress	0.3 (0.1)	0.7 (-0.1)	BBB		7.8 (0.5)		20.9 (4.0)

Notes: ML estimates of quarterly regime-switching model (5) for spanning bond returns with two states over 1995:Q1-2021:Q4. Left panel: transition matrix, right panel: annualized volatilities and correlation coefficient in each regime. Standard errors in parentheses.

Figure 11: Estimated conditional volatility of portfolio income / equity



Notes: Blue line: one-quarter-ahead estimated conditional volatility of portfolio income from regime switching model (5). Orange line: assuming the risk factors are orthogonal in the stress regime.

bond return, increases by about 50% in times of stress. The volatility of the credit-risk factor, defined as a leveraged portfolio, moves by a factor of 6, from 11% in normal times— similar to the volatility of interest-rate risk—to 62% in times of stress. The correlation between factors is zero in normal times, by construction, but declines by -55%. in times of stress. Factor realizations in normal times and times of stress are plotted as green dots and red text in Figure 1 above.

Conditional volatility as a single risk measure. We can use the conditional covariance matrix from the regime-switching model to characterize overall risk in bank portfolios and its determinants *before 2022*. The solid blue line in Figure 11 is the conditional volatility of portfolio income relative to equity for all public banks. Here we condition on the data, taking into account uncertainty about which regime is active. Income volatility increases sharply as the stress regime becomes more likely.

The key insight is that conditional income volatility is driven largely by factor volatility, with minimal impact from risk exposure variation. Outside of recessions, when the probability of stress is low, income moves only because risk exposures in Figure 7 vary over time. These income fluctuations are nonnegligible but modest. For example, we see buildups of volatility in 2003, before the financial crisis, and especially before 2022. The fluctuations here are about 10pp of equity or 25% of volatility. In contrast, the bulk of the fluctuations come from changes in the probability of the stress regime, which spikes up in bad times.

The time variation in correlations is important for overall risk. In all stress episodes before 2022, interest-rate risk exposures were hedging the vulnerability of credit-risk exposures. The orange line in Figure 11 shows conditional income volatility under the counterfactual assumption that the risk factors are orthogonal. The difference between orange and blue indicates the hedging value of the correlation, which is large at 15-20pp of equity during the typical stress episode.

The special case of 2022-3. The recent banking crisis was special in that the correlation of the two risk factors was *positive*, in sharp contrast to the earlier stress periods. The right panel of Figure 1 already showed that the 2022:Q1 was about a 4-standard deviation event under the distribution of factors that describes normal times. It is also an event exceeding 4-standard deviations under the distribution that characterizes times of stress prior to 2022. Importantly, the 2022 stress episode—marked by elevated credit spreads—coincided with high inflation, causing declines across default-free bonds, risky bonds, and stocks. For the first time since 2000, the stock-bond correlation turned positive.

We conclude that going beyond risk exposures to a single risk measure is unlikely to be fruitful. While our approach allows us to compute such measures—for example, conditional income volatility—for any statistical model of factor dynamics, the performance of any one-dimensional measure will depend heavily on the performance of that statistical model in rare times of stress, when asset prices do not always comove as they have in the past. In contrast, our approach of mapping positions into exposures with constant betas is robust to the precise model of factor dynamics. Combined with scenario analysis, it provides a way to think through stress episodes beforehand.

7.2 Measuring exposure with regressions

If risk exposures were constant at the bank level, we could bypass the calculations we have done above using balance sheet data and find risk exposures by simply regressing bank income on factors. With the regression coefficients in hand, we could again project income in different scenarios. Table 4 illustrates this approach. The first four columns show regressions of accounting portfolio income (API) relative to assets on our factors and a constant. We use data between 2001:Q1 (when OCI is first reported) and 2021:Q4. Not surprisingly, both interest-rate risk and credit-risk betas are positive and strongly significant. Interest-rate risk betas are larger after 2012 and for smaller banks.

Exposures from income regressions. The last three lines of Table 4 show that coefficients from income regressions are bad measures of risk exposures ahead of the 2022 crisis. The scenario we consider here is the *actual* path of factor realizations over 2021:Q4-2023:Q1. The annualized API over this period was about 2% of assets. With risk exposures from a regression over the sample since 2001, we would have projected 2.3%, about .6 standard deviations higher. With the post-2012 coefficients, we get closer, but are still .4 standard deviations too high. The results are even more stark for small banks: here projections are about 1.5 standard deviations too high regardless of the sample used to measure exposure.

The problem with regression-based exposures is that interest-rate risk exposures rose a lot right *before* the crisis. A regression misses this development and projects too small of a loss. The left panel of Figure 12 illustrates the issue at the individual bank level. Here we scatter actual API against projected API based on regressions of bank-level API on factors. All banks are located below the 45-degree line: regressions lead to income projections above actual income. The errors are particularly large for small and mid-sized banks that loaded up on interest-rate risk before the crisis.

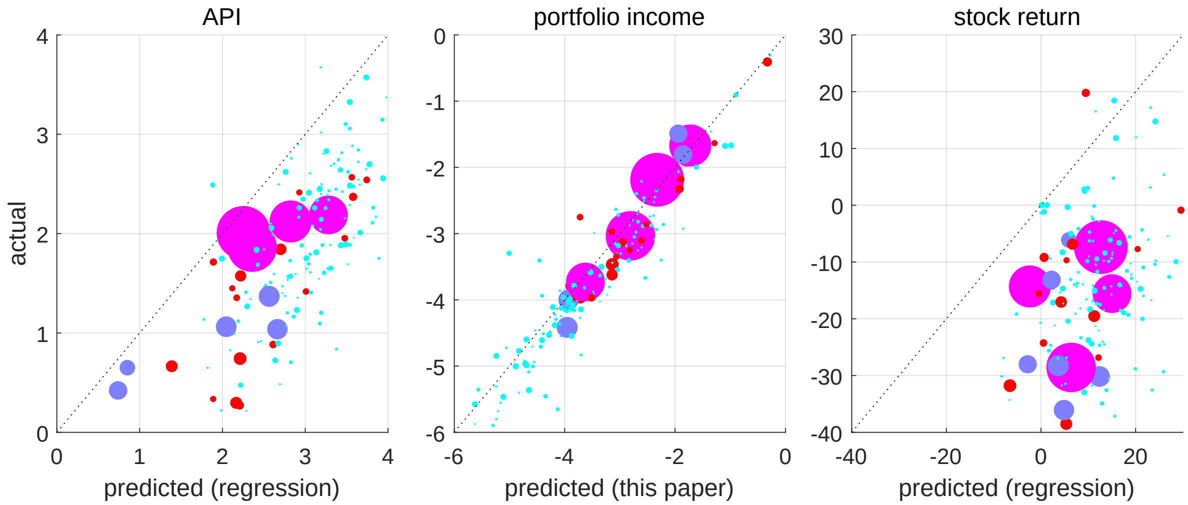
For comparison, the middle panel of Figure 12 presents out-of-sample projections of portfolio income using our own approach. As in our discussion of stress testing in Section 5.3, those projections rely on exposures we measure from balance-sheet data at the time the projection is made, here 2021:Q4. Since the scenario is again actual factor realizations, the potential source for

Table 4: Risk exposure measures from regressions

dep. var.	(income+OCI)/assets				stock returns		ΔMV/assets		ΔFV/assets	
sample	01-21	12-21	01-21	12-21	95-21	12-21	95-21	12-21	95-21	12-21
banks	all		small		all					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
int. risk	0.03	0.05	0.04	0.05	-1.01	-4.04	-0.15	-0.50	-0.28	-0.69
(t stat)	(5.2)	(9.7)	(9.5)	(10.4)	(-2.3)	(-5.8)	(-2.4)	(-6.4)	(-4.2)	(-7.9)
credit risk	0.01	0.01	0.01	0.01	0.76	0.87	0.08	0.10	0.02	0.02
(t stat)	(4.1)	(3.3)	(3.2)	(2.7)	(3.8)	(4.1)	(2.9)	(3.7)	(0.7)	(0.8)
observations	84	40	84	40	108	40	108	40	108	40
adj. R^2	0.47	0.65	0.64	0.78	0.28	0.65	0.22	0.74	0.22	0.71
	2021:Q4–2023:Q1, % p.a.									
predicted	2.29	2.17	2.76	2.68	13.17	36.99	1.81	3.41	3.28	5.72
actual	1.96	1.96	1.94	1.94	-20.32	-20.32	-2.78	-2.78	-0.09	-0.09
error (sd. dev)	-0.60	-0.37	-1.61	-1.45	-1.62	-2.77	-1.67	-2.25	-1.30	-2.23

Notes: Top panel: coefficients from regressions of average bank performance measures (percent) on interest-rate and credit-risk factors (percent) and constant (not reported) for different samples and groups of banks. Stock returns are value-weighted, all other measures are asset-weighted. Bottom panel: performance measures over 2021:Q4-2023:Q1, annualized percent, predicted = fitted value from regression, actual = from data, error = actual less predicted value divided by sample standard deviation of annualized 5-quarter value.

Figure 12: Alternative risk exposures in the cross-section of banks



Notes: Scatter plots of actual bank performance measures over 2022:Q1-2023:Q1 against out-of-sample predictions that assume the actual path of factor returns together with different exposure measures. Left panel: annualized API relative to assets, with exposures from a regression on factors with sample 2001-2021. Middle panel: annualized PI relative to assets, with exposures from our calculations for 2021:Q4. Right panel: annualized stock returns, with exposures from regressions on factors with sample 1995-2021. Dot size increases linearly with a bank's share in total bank assets if that share is larger than 20bp. Colors: pink for big 4, purple if assets > \$250bn, red if assets between \$50bn and \$250bn, light blue for all others

error is that banks adjust portfolios *during* the crisis. For most banks, this error is small. While the left and middle panels are not directly comparable, since our approach projects portfolio income and not accounting measures, the figure does underscore the advantage of measuring risk exposures in real time, rather than from a regression.

Exposures from stock-return regressions. Columns 5 and 6 of Table 4 follow a large literature by measuring bank-risk exposures from stock-return regressions. Like income, bank stock returns comove strongly with the credit-risk factor. In contrast to income, however, they move *against* the interest-rate risk factor. The slope coefficient is only borderline significant over the full sample but becomes significantly negative after 2012. Bank stocks thus behave much like the overall stock market. The period 2000-20 is well known for a strongly negative bond-stock correlation (and bond beta). The explanatory power of the two factors for stock returns is low (22%) over the whole sample but high (68%) over the more recent sample.

Stock-return regressions also produce poor measures of exposure at the beginning of the 2022 crisis. The actual stock return for all public banks over 2021:Q4-2023:Q1 was -20%. The last three rows of Table 4 show projections under the scenario of actual factor realizations which deliver sizeable *positive* returns. With the full sample coefficients, we would have projected a 13% return, slightly above the sample mean of 11% and more than 1.5 standard deviations too high. The right panel of Figure 12 plots actual against predicted returns at the bank level to show that this is a general pattern. Moreover, with exposures based on the post-2012 sample, we would have projected a 36% return, more than 2.5 standard deviations too high. Focusing on recent data worsens the performance of this method, unlike for income.

The role of franchise value. What determines exposure measures from stock-return regressions? If the value of a bank were just its fixed-income position, we would expect positive exposure to interest-rate risk and more accurate projections when using the recent sample, much like for income. However, the value of a bank also contains the value of nonfinancial assets and intangibles, such as rents due to market power or adjustment costs. The left panel of Figure 13 plots the cross-sectional relationship between the fixed-income position and the market value of equity at the end of 2021. For the average bank, the market value is twice as large as its fixed-income position.

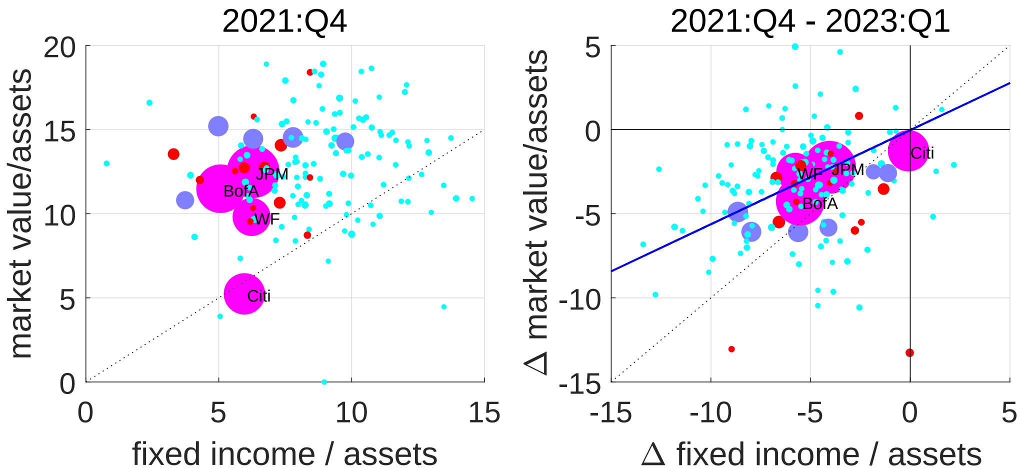
We define the *franchise value* of a bank as the difference between its market value of equity and the sum of its fixed-income position and the book value of net nonfinancial assets. As a by-product of our valuation approach, we obtain a time series for the franchise value of each bank. Appendix E presents summary statistics. The franchise value is a volatile component of bank value that is highly correlated with the market value of equity, whereas nonfinancial assets are fairly stable. At the end of 2021, the franchise value alone made up 21% of market value for all banks and 27% for the group of small banks ranked 50 and lower.

The poor performance of exposure measures from stock return regressions is largely due to the unusual dynamics of franchise value over the last 15 years. We illustrate this in the last four columns of Table 4. Since franchise values can be negative or small, it is not practical to work with returns on the franchise. We thus prefer to work with changes in value relative to assets.[16] To verify that those measures capture the same forces as returns, we first consider regressions of market-value changes on factors in columns 7 and 8 of Table 4. These results exhibit the same patterns as regressions with stock returns in columns 5 and 6.

Before 2022, franchise values contained a large short position in interest-rate risk. Columns 9 and 10 of Table 4 show exposure measures from regressions of franchise-value changes on factors. Over both the full and the recent sample, we obtain strong and highly significant negative exposure

[16] In principle, one could form a return on a bank's fixed-income position and its non-fixed income assets and then back out a franchise return from the stock returns. Since both the fixed-income position and the franchise value can become negative, however, those measures tend to be volatile and are not well suited for regression analysis. Moving to value changes avoids this technical issue without losing key economic properties.

Figure 13: Comovement of market values with fixed-income positions



Notes: Scatter plot of equity market value against (net) fixed-income position in 2021:Q4 (left panel) and change in equity market value against change in (net) fixed-income position over 2021:Q4-2023:Q1, all as a percentage of assets in 2021:Q4, for all public banks (right panel). Dot size increases linearly with a bank's share in total bank assets if that share is larger than 20bp. Colors: pink for big 4, purple if assets >\$250bn, red if assets between \$50bn and \$250bn, light blue for all others.

to the interest-rate factor. Coefficients on the credit-risk factor are small and insignificant. Over the recent sample, the R^2 is also high at 72%. Between the financial crisis and the recent banking crisis, the franchise value looks like a short position in default-free bonds. Over the whole sample, the explanatory power of the factors is weak at only 24%. In other words, bank rents are affected by other forces that do not show up in portfolio risk.

Regardless of the sample, exposures measured from regressions poorly project franchise value forward. Based on actual realizations, we would have predicted much larger franchise value losses: by .9 standard deviations using the full sample and 1.5 standard deviations under the recent sample. Franchise values, like stock market values, are strongly negatively associated with interest-rate risk in the recent sample. In the 2022 crisis, however, franchise values moved little when the value of interest-rate positions fell dramatically, in sharp contrast to the tight negative correlation that the regression picks up.[17]

The right panel of Figure 13 clarifies the strong comovement of market values with fixed-income positions over the recent crisis. The blue asset-weighted regression line has a slope of 0.55. Appendix E presents decompositions at the bank-group level. Outside of the big 4 banks, fixed-income losses account for more than 80% of the market-value decline. Even for the big 4

[17]This finding is related to the time-varying correlation between stocks and bonds that has been documented in the literature (e.g., David and Veronesi 2013).

banks, fixed-income losses account for more than 60% of the market-value declines.

We conclude that stock return regressions do not provide a fruitful way to measure banks' exposures to our risk factors. This is perhaps because the approach is too ambitious: it assumes stability over time not only of portfolio-risk exposures—which we have already seen vary over time—but also of franchise-value dynamics. The latter, however, appears to depend on other bank features and their time-varying correlation with the macroeconomy that are separate from bank portfolio risk. Since exposures through franchise values cannot be directly measured but must be modeled statistically, we run into the instability issues we have documented. Our approach instead provides a robust way to describe bank portfolios, a part of bank value that can be directly and robustly measured.

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Appendix

A Return data

Returns on Treasuries and swaps are computed from price data. Treasury zero-coupon bond prices for all maturities are from the Federal Reserve Board website. The source of all other return data is Bloomberg. For the returns on swap-quality bonds, we start from data on yields. LIBOR rates have maturities of three months and six months. Swap yields have annual maturities between 1 and 10 years, then 12, 15, 20, 25, and 30 years. In each quarter, we interpolate the yield curve for Treasuries and swap-quality bonds so that we have bond-price data P_t^n for all quarterly maturities n up to $30 \times 4 = 120$ quarters, which allows us to compute returns $P_{t+1}^{n-1}/P_t^n - 1$. The returns for bonds in a maturity bucket (such as "short" bonds with maturities 1-3 years in Table A.1) are the equally-weighted returns on bonds with maturities in that bucket.

The returns on risky bonds are by credit quality: AAA, AA, A, BBB, BB, B and C+. For each credit quality, Bank of America Merrill Lynch provides a "total return index" that tracks the actual return on a bond investment for various maturity buckets (years 1-3, 3-5, 5-7, 7-10, 10-15 and 15+ years). Using notation P_t for the index, we compute returns $P_{t+1}/P_t - 1$. The returns data on mortgage-backed securities have the same maturity buckets, with a few missing observations for intermediate maturities, and are also constructed by BofA Merrill Lynch. The sample starts in 1990:Q2, when BofA Merrill Lynch begins providing returns data, and ends in 2024:Q1.

Summary statistics. Table A.1 reports summary statistics for bond returns binned by maturity (in column 1) and credit rating (column 2). Column 3 shows annualized mean returns, while column 4 shows unconditional volatility. We recover two familiar patterns. First, holding credit quality constant, longer maturity bonds have returns with higher mean and higher volatility. Second, holding maturity constant, lower-rated bonds have returns with higher mean and higher volatility. Both interest-rate risk (due to longer duration) and credit risk (due to lower credit quality) thus generate volatility for which bond investors are compensated with higher mean returns. Finally, mortgage-backed securities backed by U.S. agencies are comparable to highly rated bonds.

Table A.1: Properties of returns on fixed-income instruments

(1)	(2)	mean (in %) (3)	vol (in %) (4)	β^{swap} (5)	t-stat (6)	β^{BBB} (7)	t-stat (8)	R^2 (9)	R^2 /w 1 factor (10)	p-value (11)
Treas	short	3.8	2.4	0.36	15.6	0.01	0.3	0.79	0.79	0.03
	medium	5.8	6.5	1.08	27.6	−0.02	−0.6	0.96	0.96	0.80
	long	7.7	12.0	1.78	17.1	−0.14	−1.5	0.73	0.73	0.42
Swaps	short	4.1	2.7	0.40	22.8	0.02	1.3	0.82	0.82	0.01
	medium	6.1	6.9	1.17	108.8	−0.02	−1.9	0.99	0.99	0.12
	long	8.1	13.2	2.19	29.3	−0.27	−3.8	0.89	0.88	0.58
AAA	short	4.2	2.4	0.30	14.0	0.11	3.5	0.76	0.70	0.21
	medium	5.9	5.4	0.75	19.8	0.19	3.0	0.85	0.81	0.54
	long	6.8	8.5	1.19	12.2	0.02	0.1	0.70	0.70	0.27
BBB	short	4.9	3.2	−0.03	−1.2	0.56	18.4	0.88	0.10	0.80
	medium	6.6	6.2	−0.00	−0.34	1.14	104.7	0.99	0.14	0.33
	long	7.4	7.9	0.20	3.2	1.28	15.7	0.90	0.24	0.67
MBS	short	4.4	2.6	0.31	10.0	0.10	3.3	0.66	0.62	0.99
	medium	4.9	4.0	0.55	12.6	0.13	2.1	0.81	0.78	0.15
	long	4.8	3.5	0.49	21.9	0.13	5.2	0.85	0.82	0.17

Note: The sample is quarterly data from 1990:Q2 to 2024:Q1. Columns 1 and 2 of this table indicate the instrument that is being considered. "Short" refers to maturities between 1 and 3 years, "medium" refers to 5-7 years, and "long" to 10-15 years. Columns 3 and 4 report the mean return and its standard deviation per year. Columns 5-9 report the results from exposure regressions

$$r_t^i = \alpha_i + \beta_i^{\text{swap}} r_t^{swap} + \beta_i^{\text{BBB}} r_t^{\text{BBB}} + u_t^i,$$

where r_t^{swap} is the demeaned return on a 5-year swap-quality bond and r_t^{BBB} is the demeaned return on a 5-year BBB rated bond. Column 10 reports the R^2 from regressions on only the interest-rate factor based on the entire sample. Column 11 reports the p-value of the Engle test for heterokedasticity.

Factor structure in returns. Table A.1 also establishes our first stylized fact: the two spanning-bond returns explain most variation in any other bond return. Columns 5 and 7 show the slope coefficients of a regression of each return on a constant and the returns on the two spanning bonds. Columns 6 and 8 report the associated t-statistics. The R^2s reported in column 9 are above 70 percent for investment grade bonds of all available maturities (BBB rated or higher) and around 90 percent for most of these maturities. The swap-quality bond return (which is our interest-rate risk factor) alone explains above 70 percent of the return variation on prime bonds of all maturities (Treasuries, swaps and other AAA-rated bonds), as column 10 shows.[18]

B Details on replication procedure

This appendix describes the details of our replication procedure for all bank positions except interest-rate derivatives, which we cover in the separate Appendix D, and credit derivatives, which we cover in Appendix C. Section B.1 describes our data sources and sample selection. Section B.2 presents the inputs to our replication procedure: position values, maturity, and credit quality. Section B.3 explains how we first use those inputs to prepare value distributions by maturity and credit quality. Section B.4 then shows how we replicate the positions implied by those distributions.

B.1 Data sources and sample selection

Data on bank holding companies. In the U.S., bank holding companies (BHCs) file quarterly regulatory reports (form FR-Y-9C). These reports contain standard financial reporting schedules such as balance sheets (Schedule HC-B in Figure A.1) and income statements (Schedule HC-I). BHCs often have commercial bank subsidiaries that file call reports (form FFIEC 031/041). Commercial bank filings provide more detailed information on some line items. We thus match all commercial banks belonging to the same BHC to their parent. For publicly traded banks, we have data on market capitalization and stock returns from CRSP, using the Federal Reserve Bank of New York link data to match a BHC to market data from CRSP.[19]

Ownership structure. A BHC often owns one or more commercial banks or other BHCs. We consider only BHCs that are the "top tier" company in their BHC and eliminate any BHC owned by another BHC or a foreign parent. Up to 2010, the commercial bank call report forms included detailed information about banks' ownership structure. From 2011 to 2021:Q2, the Federal Reserve Bank of Chicago published commercial bank structure data files that contained ownership structure data in the same form. Since 2021:Q3, structure data, including bank attributes and ownership information, are found on the data download page of the National Information Center (NIC) website.

Sample. Our baseline sample consists of all publicly traded BHCs for the period from 1995:Q1

[18] We do not need to take a stand on what accounts for the remaining variation. It is possible, for example, that one can find a third factor that generates common variation in low-quality returns. Since our approach employs a linear framework, the results are valid regardless of where the additional variation comes from and would also be relevant if other factors were added later.

[19] https://www.newyorkfed.org/research/banking_research/crsp-frb

through 2024:Q1. We only keep the domestic top-tier BHC entities in the ownership structure. In total, 963 BHCs appear at least once in our baseline panel. The average number of BHCs in a quarter is 372. The number ranges between a low of 174 in 2024:Q1 and a high of 523 in 1999:Q2.

Merger data. The NIC website publishes data on mergers in a CSV file called "Transformations." This file is periodically updated and contains the date and the reason for the transformation (e.g., merger, acquisition, split, or failure) and the ID numbers (rssd9001) of the involved parties, i.e., the surviving (successor) and non-surviving (predecessor) rssd9001 numbers. We convert the daily event date to quarterly and merge this data to the commercial bank sample. Information on mergers is relevant for estimating the risk exposures of loans and derivatives. For those positions, the available information at a point in time is not sufficiently detailed. We use the bank's history to inform our inference. Sections B.4 and D.4 discuss this in further detail below.

Figure A.1: FR-Y-9C Balance Sheet: Assets

Schedule HC—Consolidated Balance Sheet

Dollar Amounts in Thousands		BHCK	Bil	Mil	Thou	
Assets						
1. Cash and balances due from depository institutions:						
a. Noninterest-bearing balances and currency and coin[1]		0081				1.a.
b. Interest-bearing balances:[2]						
(1) In U.S. offices		0395				1.b.(1)
(2) In foreign offices, Edge and Agreement subsidiaries, and IBFs		0397				1.b.(2)
2. Securities:						
a. Held-to-maturity securities (from Schedule HC-B, column A)		1754				2.a.
b. Available-for-sale securities (from Schedule HC-B, column D)		1773				2.b.
3. Federal funds sold and securities purchased under agreements to resell:						
a. Federal funds sold in domestic offices	BHDM	B987				3.a.
b. Securities purchased under agreements to resell[3]	BHCK	B989				3.b.
4. Loans and lease financing receivables:						
a. Loans and leases held for sale		5369				4.a.
b. Loans and leases, net of unearned income	B528					4.b.
c. LESS: Allowance for loan and lease losses	3123					4.c.
d. Loans and leases, net of unearned income and allowance for loan and lease losses (item 4.b minus 4.c)		B529				4.d.
5. Trading assets (from Schedule HC-D)		3545				5.
6. Premises and fixed assets (including capitalized leases)		2145				6.
7. Other real estate owned (from Schedule HC-M)		2150				7.
8. Investments in unconsolidated subsidiaries and associated companies		2130				8.
9. Direct and indirect investments in real estate ventures		3656				9.
10. Intangible assets:						
a. Goodwill		3163				10.a.
b. Other intangible assets (from Schedule HC-M)		0426				10.b.
11. Other assets (from Schedule HC-F)		2160				11.
12. Total assets (sum of items 1 through 11)		2170				12.

Notes: This figure presents a snapshot of the FR-Y-9C regulatory report schedule HC (consolidated balance sheet) assets. This schedule is from the December 2015 report.

B.2 Regulatory data on value, maturity and credit quality

In this section, we describe how regulatory filings report the value of bank assets and liabilities and what information is available about banks' credit quality and maturity.

Fair values and face values for securities, loans, and debt. Our calculations require positions' market value (fair value) as an input, while accounting rules allow banks to report some positions only in terms of book values. The Federal Accounting Standards Board's statement 115, issued in 1993, introduced a three-way split of loan and securities positions into "held to maturity", "available for sale", and "held for trading" instruments. Held-for-trading and available-for-sale positions are recorded at fair value since banks intend to hold those only briefly.[20]

Held-to-maturity instruments may instead be recorded on the balance sheet at face value or amortized cost. The face value for a typical installment loan is the amount of money disbursed when the loan is taken out. The face value for a typical coupon bond is the amount repaid at maturity.

Regulatory filings require a breakdown into the three categories for both loans and securities. For securities, BHCs must always provide fair value estimates regardless of how they categorize positions. This information is contained in Schedule HC-B of Form FR-Y-9C, shown in Figure A.2. In contrast, banks' loan portfolios as well as term deposits and other borrowed money are primarily reported on bank balance sheet as face values. Section B.4 below explains how we convert those book values to market values.

[20] The difference between available-for-sale and held-for-trading assets is how changes in fair values affect earnings. Trading gains and losses directly affect net income, whereas gains and losses on available-for-sale assets enter other comprehensive income, a component of equity.

Figure A.2: Details on Banks' Investment Securities from FR-Y-9C Schedule HC-B

Schedule HC-B—Securities

	Held-to-Maturity		Available-for-Sale		
	(Column A) Amortized Cost	(Column B) Fair Value	(Column C) Amortized Cost	(Column D) Fair Value	
Dollar Amounts in Thousands	BHCK Bil Mil Thou	BHCK Bil Mil Thou	BHCK Bil Mil Thou	BHCK Bil Mil Thou	
1. U.S. Treasury securities	0211	0213	1286	1287	1.
2. U.S. government agency obligations (exclude mortgage-backed securities):					
a. Issued by U.S. government agencies[1]	1289	1290	1291	1293	2.a.
b. Issued by U.S. government-sponsored agencies[2]	1294	1295	1297	1298	2.b.
3. Securities issued by states and political subdivisions in the U.S.	8496	8497	8498	8499	3.
4. Mortgage-backed securities (MBS)					
a. Residential pass-through securities:					
(1) Guaranteed by GNMA	G300	G301	G302	G303	4.a.(1)
(2) Issued by FNMA and FHLMC	G304	G305	G306	G307	4.a.(2)
(3) Other pass-through securities	G308	G309	G310	G311	4.a.(3)
b. Other residential mortgage-backed securities (include CMOs, REMICs, and stripped MBS):					
(1) Issued or guaranteed by U.S. Government agencies or sponsored agencies[3]	G312	G313	G314	G315	4.b.(1)
(2) Collateralized by MBS issued or guaranteed by U.S. Government agencies or sponsored agencies[3]	G316	G317	G318	G319	4.b.(2)
(3) All other residential mortgage-backed securities	G320	G321	G322	G323	4.b.(3)
c. Commercial MBS:					
(1) Commercial pass-through securities:					
(a) Issued or guaranteed by FNMA, FHLMC, or GNMA	K142	K143	K144	K145	4.c.(1)(a)
(b) Other pass-through securities	K146	K147	K148	K149	4.c.(1)(b)
(2) Other commercial MBS:					
(a) Issued or guaranteed by U.S. Government agencies or sponsored agencies[3]	K150	K151	K152	K153	4.c.(2)(a)
(b) All other commercial MBS	K154	K155	K156	K157	4.c.(2)(b)

1. Includes Small Business Administration "Guaranteed Loan Pool Certificates," U.S. Maritime Administration obligations, and Export-Import Bank participation certificates.
2. Includes obligations (other than mortgage-backed securities) issued by the Farm Credit System, the Federal Home Loan Bank System, the Federal Home Loan Mortgage Corporation, the Federal National Mortgage Association, the Financing Corporation, Resolution Funding Corporation, the Student Loan Marketing Association, and the Tennessee Valley Authority.
3. U.S. Government agencies include, but are not limited to, such agencies as the Government National Mortgage Association (GNMA), the Federal Deposit Insurance Corporation (FDIC), and the National Credit Union Administration (NCUA). U.S. Government-sponsored agencies include, but are not limited to, such agencies as the Federal Home Loan Mortgage Corporation (FHLMC) and the Federal National Mortgage Association (FNMA).

Schedule HC-B—Continued

	Held-to-Maturity		Available-for-Sale		
	(Column A) Amortized Cost	(Column B) Fair Value	(Column C) Amortized Cost	(Column D) Fair Value	
Dollar Amounts in Thousands	BHCK Bil Mil Thou	BHCK Bil Mil Thou	BHCK Bil Mil Thou	BHCK Bil Mil Thou	
5. Asset-backed securities and structured financial products:					
a. Asset-backed Securities (ABS)	C026	C988	C989	C027	5.a.
b. Structured financial products:					
(1) Cash	G336	G337	G338	G339	5.b.(1)
(2) Synthetic	G340	G341	G342	G343	5.b.(2)
(3) Hybrid	G344	G345	G346	G347	5.b.(3)
6. Other debt securities:					
a. Other domestic debt securities	1737	1738	1739	1741	6.a.
b. Other foreign debt securities	1742	1743	1744	1746	6.b.
7. Investments in mutual funds and other equity securities with readily determinable fair values			A510	A511	7.
8. Total (sum of 1 through 7) (total of column A must equal					

Notes: This figure presents a snapshot of the FR-Y-9C report schedule HC-B (securities schedule). This schedule is from the December 2015 report.

Fair values and notionals for derivatives. We retrieve notional values and fair values for interest-rate and credit derivatives from Schedule HC-L of Form FR-Y-9C, shown in Figure A.3. Appendices D and C describe the relevant line items for interest-rate derivatives and credit derivatives, respectively.

The information in Schedule HC-L is more comprehensive than what banks report about derivatives on their balance sheet, for two reasons. First, derivatives are reported on the balance sheet only when they are "held for trading". Any positions with positive (negative) fair value are then reported as part of trading assets (liabilities).[21] Derivatives not-held-for-trading remain "off-balance-sheet" and reported only in Schedule HC-L. Second, for-trading derivatives on the balance sheet contain only "freestanding" derivatives, whereas "embedded" derivatives are included on the balance sheet under "other assets". Schedule HC-L, in contrast, contains both types.[22]

Maturity data. For information about the maturity or time-to-repricing of assets, we rely on commercial bank call reports (Form FFIEC 031). Bank-level call reports provide a finer maturity decomposition for securities than the BHC-level FR-Y-9C reports, and moreover provide maturity data for loans. As an example, Figure A.4 shows the reporting form for the maturity decomposition of a bank's loan portfolio. Loans are sorted into six buckets according to maturity (for fixed-rate loans) or time to next repricing (for floating-rate loans): within three months or less, more than three months, up to 12 months, over one year to three years, over three years to five years, over five years to 15 years, and beyond 15 years. For securities, maturity information follows the same format and is reported separately for MBS and non-MBS securities. For any given BHC, we aggregate face values of loans or fair values of securities of all commercial bank subsidiaries to the parent BHC level. For most banks, commercial bank aggregates closely match totals from the BHC's FR-Y-9C report.[23]

Figure A.5 shows the maturity distribution for aggregate holdings of securities (left panel) and loans (right panel). The total amount of security holdings and loans has increased over time. During the 1990s, holdings of securities were roughly equally distributed across maturities. During

[21]For derivatives, the scope of the term "held-for-trading" is broad. The Federal Reserve Board's Guide to the BHC performance report states: "Besides derivative instruments used in dealing and other trading activities, this line item (namely, derivatives held for trading purposes) covers activities in which the BHC acquires or takes derivatives positions for sale in the near term or with the intent to resell (or repurchase) in order to profit from short-term price movements, accommodate customers' needs, or hedge trading activities".

[22]The reporting instructions state "Holding companies must report the notional amounts of their derivative contracts (both freestanding derivatives and embedded derivatives that are accounted for separately from their host contract under ASC Topic 815) by risk exposure in Schedule HC-L." Source.

[23]Occasionally, a BHC-quarter observation does not have a matching commercial bank observation, and therefore, we do not have information on the loans and securities maturity distribution for that bank. For these BHC-quarter observations, we fill the missing loan and security maturity values with the maturity distribution of the aggregate loan and security distribution, scaled to the loan and security level of the BHC in that quarter.

Figure A.3: HC-L Banks' Derivative Positions

Schedule HC-L—Continued

Dollar Amounts in Thousands	(Column A) Interest Rate Contracts	(Column B) Foreign Exchange Contracts	(Column C) Equity Derivative Contracts	(Column D) Commodity and Other Contracts	
Derivatives Position Indicators	Tril Bil Mil Thou	Tril Bil Mil Thou	Tril Bil Mil Thou	Tril Bil Mil Thou	
11. Gross amounts (e.g., notional amounts) (for each column, sum of items 11.a through 11.e must equal sum of items 12 and 13):					
a. Futures contracts.......	BHCK 8693	BHCK 8694	BHCK 8695	BHCK 8696	11.a.
b. Forward contracts......	BHCK 8697	BHCK 8698	BHCK 8699	BHCK 8700	11.b.
c. Exchange-traded option contracts:					
(1) Written options.....	BHCK 8701	BHCK 8702	BHCK 8703	BHCK 8704	11.c.(1)
(2) Purchased options..	BHCK 8705	BHCK 8706	BHCK 8707	BHCK 8708	11.c.(2)
d. Over-the-counter option contracts:					
(1) Written options.....	BHCK 8709	BHCK 8710	BHCK 8711	BHCK 8712	11.d.(1)
(2) Purchased options..	BHCK 8713	BHCK 8714	BHCK 8715	BHCK 8716	11.d.(2)
e. Swaps....................	BHCK 3450	BHCK 3826	BHCK 8719	BHCK 8720	11.e.
12. Total gross notional amount of derivative contracts held for trading......	BHCK A126	BHCK A127	BHCK 8723	BHCK 8724	12.
13. Total gross notional amount of derivative contracts held for purposes other than trading...........	BHCK 8725	BHCK 8726	BHCK 8727	BHCK 8728	13.
14. Gross fair values of derivative contracts:					
a. Contracts held for trading:					
(1) Gross positive fair value..................	BHCK 8733	BHCK 8734	BHCK 8735	BHCK 8736	14.a.(1)
(2) Gross negative fair value..................	BHCK 8737	BHCK 8738	BHCK 8739	BHCK 8740	14.a.(2)
b. Contracts held for purposes other than trading:					
(1) Gross positive fair value..................	BHCK 8741	BHCK 8742	BHCK 8743	BHCK 8744	14.b.(1)
(2) Gross negative fair value..................	BHCK 8745	BHCK 8746	BHCK 8747	BHCK 8748	14.b.(2)

Notes: This figure presents a snapshot of the FR-Y-9C report schedule HC-L (Derivatives and Off Balance-Sheet-Items) items 11 through 14 (Notionals and fair value by derivative types). This schedule is from the December 2015 report.

2001-2007, when interest rates increased, securities holdings became more long-term. Another increase in long-term security holdings came after 2020, coinciding with the recent surge in deposits.

Figure A.4: Loan Maturities and Repricing Buckets FFIEC 031/41 Schedule RC-C Memoranda item

Schedule RC-C—Continued

Part I—Continued

Memoranda—Continued

Dollar Amounts in Thousands	RCON	Bil	Mil	Thou	
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)

Notes:This figure presents a snapshot of the call report schedule RC-C (loan schedule) and its memoranda item 2. This schedule is from the December 2015 report form FFIEC 031.

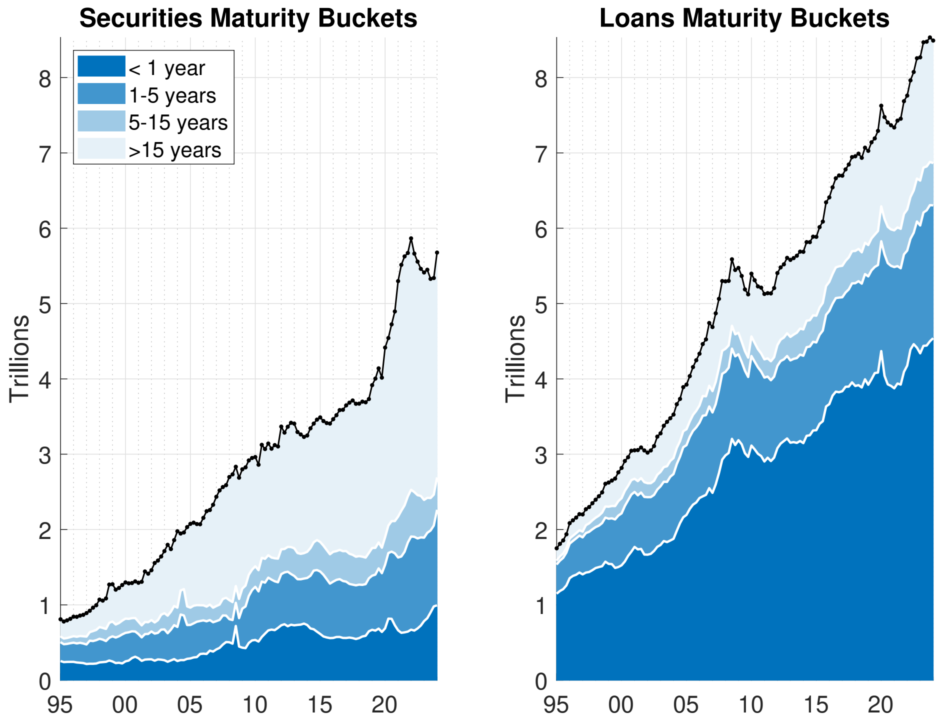
While most loans remained short-term during our sample period, their average maturity increased slightly after the financial crisis. For example, the maturity of commercial and industrial loans has increased over the years (see, for example, the E.2 release by the Board of Governors of the Federal Reserve System, available until 2017.)

We obtain information about the maturity of liabilities from the BHC's FR-Y-9C report. In particular, detail on deposits is from memoranda to Schedule HC-E and on other borrowed money from Schedule HC-M.[24]

Credit quality data. Schedules HC-B and Schedule HC-D of the FR-Y-9C reports contain fair values of Treasury securities and Agency MBS, respectively. For other positions, we obtain information on credit quality from Schedule HC-R Part 2 ("Risk-Weighted Assets") of BHCs'

[24] From schedule HC-M, other borrowed money is allocated to three maturity buckets: commercial paper (BHCK2309), other borrowed money with a remaining maturity of one year or less (BHCK2332), and other borrowed money with a remaining maturity of more than one year (BHCK2333). We allocate each bucket amount evenly across a quarterly maturity distribution, assuming that commercial papers are at most one quarter long, and that the maximum maturity of other borrowed money is five years.

Figure A.5: Holdings of securities and loans of U.S. banking sector by maturity bucket



Notes: This figure shows the loan and security holdings by maturity bucket in trillion dollars. Left panel: market value of securities and trading assets. Right panel: face value of loans.

FR-Y-9C reports. Here BHCs assign asset positions to risk-weight buckets that regulators then use to calculate risk-weighted capital requirements. The instructions for filling out Schedule HC-R relate risk weights to credit ratings issued by the major rating agencies. We display the form from the year 2005 in Figure A.6. For example, a position in the 100% risk-weight bucket is equivalent to a BBB-rated security.

The number of risk weight buckets has changed during our sample period. Up until 2014:Q4, risk-weight buckets were 0%, 20%, 50%, and 100%, with an additional bucket for unrated assets and adjustments. After 2015, Schedule HC-R was expanded: there are now additional buckets for higher risk weights, up to 150% for loans and 1250% for securities. In addition, banks sometimes rate loans at risk weights that do not align with a particular bucket using the unrated bucket as an offset.[25] However, very few loans and securities are rated worse than BBB throughout our sample. Figure A.7 presents a breakdown of risk-weight shares for all bank assets. According to the regulatory filings, most risk-weighted assets have a credit rating of BBB or better. Moreover, the

[25]For example, before 2015 banks were instructed to rate certain loans at 200%. Since a bucket of 200% did not yet exist, banks recorded twice the face value of the loans in the 100% risk bucket and then subtracted the face value from the unrated bucket, which therefore could contain negative numbers.

Figure A.6: Call report instructions for risk weight to credit rating conversion

Long-Term Rating Category	*Examples*	*Risk Weight*
Highest or second highest investment grade	AAA or AA	20%
Third highest investment grade	A	50%
Lowest investment grade	BBB	100%
One category below investment grade	BB	200%
More than one category below investment grade, or unrated	B or unrated	Not eligible for ratings-based approach

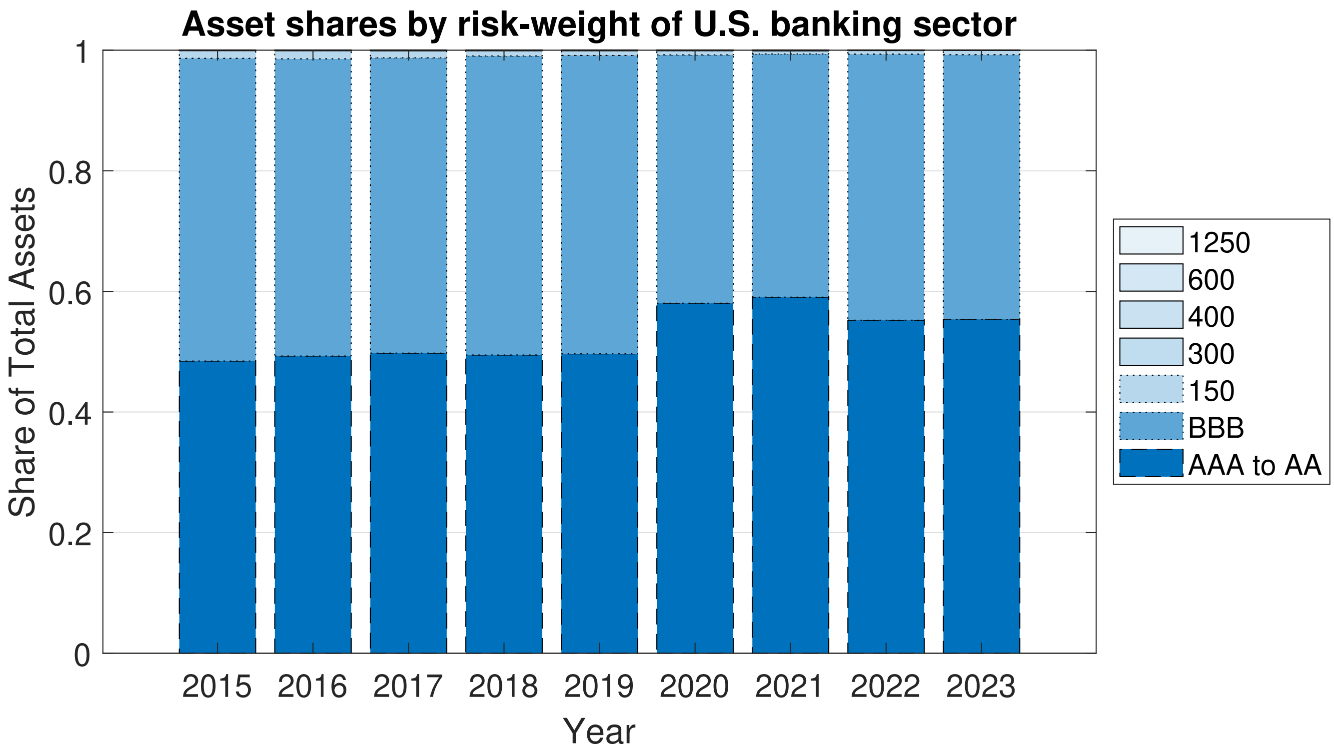
Short-Term Rating Category	*Examples*	*Risk Weight*
Highest investment grade	A-1, P-1	20%
Second highest investment grade	A-2, P-2	50%
Lowest investment grade	A-3, P-3	100%
Below investment grade, or unrated	B or unrated	Not eligible for ratings-

Notes: This figure is an excerpt from the 2005 March Instructions for FR-Y-9C filers.

unrated bucket contains mostly non-fixed-income assets such as bank real estate and intangibles and only very few securities or loans. The mean share of unrated positions as a share of total loans and securities is below one percent. We thus work with BBB as the worst relevant rating for loans and securities and add the small share of worse-rated positions to the BBB positions.

Figure A.8 presents the resulting breakdown into risk classes for securities (left panel) and loans (right panel). Since 2000, the share of risky loans and securities has increased, whereas investments in low-risk securities such as Treasuries have remained constant until the crisis. High-risk securities, with a risk weight of at least 100%, and Agency MBS rose during the housing boom between 2000 and 2007. Since the financial crisis, the share of liquid securities such as Treasury

Figure A.7: Asset shares by risk-weight of U.S. banking sector



Notes: This figure presents the share of individual risk-weights for all risk-weighted assets since 2015 for the aggregate banking sector. The share of assets with risk-weights lower than 100% are indicated as $AAAtoAA$, and assets with a risk-weight of 100% are indicated as BBB. The remaining risk weights (all higher than 100%) are indicated in the legend.

securities and agency MBS has increased. Banks' loan portfolio consists mostly of high-risk loans (with a risk weight of at least 100%) whose loan portfolio share has been increasing over our sample period.

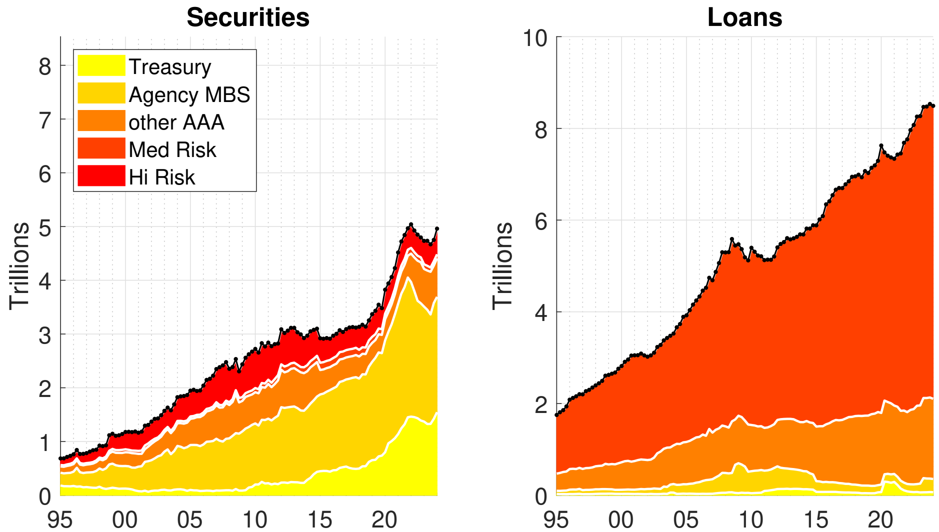
B.3 Distributions of positions by credit quality and maturity

In this section, we describe how we use the data introduced in Section B.2 to calculate distributions of value by credit quality and maturity for loans, debt, and securities. For loans and debt, we build distributions of face values that will be converted into fair values in a separate step, described below in Section B.4.

Face value distributions for loans. Our loan valuation relies on distributions of face values by credit quality and maturity, measured in quarters.[26] To infer the joint distribution for each bank,

[26]Note that unlike for the replication of securities, the loan portfolio replication requires only maturity information as shown in Appendix Section B.4.

Figure A.8: Holdings of securities and loans of U.S. banking sector by risk-weight



Notes: This figure shows the asset share of securities (left panel) and loans (right panel) by risk-weight bucket according to Schedule HC-R. Colors reflect risk classes described in top-left legend.

we start from the reported maturity and credit breakdown of its loan portfolio and incorporate information on the key characteristics of the most common loan types. Note that maturity refers to the contractual maturity for fixed-rate loans and to time to repricing for floating-rate loans.

The most common loan type is the residential mortgage. Mortgages are typically fixed-rate loans with 15- to 30-year terms; they are securitized and, under regulatory risk-weighting frameworks, are generally considered to carry low credit risk.[27] Commercial and industrial (C&I) loans are the second most common type of bank loan. They are typically structured as floating-rate loans with shorter maturities than residential mortgages and generally carry investment-grade credit risk. [28] Credit card loans are floating rate loans with short maturities, and are also typically riskier than mortgages since they are unsecured.

Given the typical characteristics of loan types, we expect credit quality to be negatively cor-

[27]Regulatory risk-weights for mortgage are lower than risk-weights for C&I loans, see Table 1 in `https://www.bis.org/bcbs/publ/d363.pdf`.

[28]Based on available data from the Senior Loan Officer Survey on Lending Practice, the weighted average maturity of C&I loans over the 1997-2017 period ranged from less than a year to less than three years (see `https://fred.stlouisfed.org/series/EDANQ`). Only 50% of C&I loans are considered loans with moderate or "other" risks as opposed to low risk. To obtain the 50% number, we downloaded the series EVAMXDBNQ (total value C&I loans moderate credit risk), EVAONQ (total value C&I loans with other risk), and EVANQ (total value C&I loans) from the St. Louis Fed, and computed the average ratio of moderate and other to total loans. According to the Shared National Credit Report (`https://www.occ.treas.gov/publications-and-resources/publications/shared-national-credit-report/files/shared-national-credit-report-2024.pdf`) banks' syndicated loan portfolios consist mainly of investment grade equivalent revolvers (i.e., floating rate loans).

related with maturity for fixed-rate loans and with time to repricing for floating-rate loans. To construct the joint credit–maturity distribution of the loan portfolio, we recursively assign riskier loan face value positions to the shortest maturity buckets first. We ensure that the joint distribution is consistent with the marginal distributions reported in the call reports.

Specifically, we start with BBB-rated loans. If the total face value of all BBB loans exceeds or equals loans in the shortest maturity bucket (with maturity or repricing date below one quarter), we assume all BBB-rated loans are one-quarter loans. Consequently, no loan in our three remaining risk categories (AAA, AA, and A) can be short-term. In cases where a bank reports more BBB loans than short-term loans, we assume that the excess BBB loan amounts (beyond the one-quarter bucket) have maturities ranging from two quarters to 120 quarters based on the proportional distribution of loan values within that range. Similarly, all loans rated AAA, AA, and A are allocated entirely to long-term maturity buckets (two to 120 quarters).

Conversely, if the total face value of BBB-rated loans is less than the amount in the shortest maturity bucket, we assume that all BBB loans mature or reprice within one quarter, and none are allocated to longer-term maturity buckets. Any remaining short-term loans (exceeding the total BBB loan amounts) are then proportionally distributed across the three safer risk-weight buckets (AAA, AA, and A) according to their respective shares. Similarly, the remaining non-short safe loans are allocated entirely to long-term maturity buckets. Note that our time series and cross-sectional facts are qualitatively robust to using a uniform joint distribution.

Face value distributions for debt. We treat banks' long-term debt similar to loans, assuming that bank debt has a AAA rating. We measure the maturity distribution from the call reports and distribute values evenly across quarters within the same maturity bucket.

Fair value distributions for securities. For securities, we observe fair values. Our replication approach maps each fair value position of a certain duration and credit quality into our two factors. We thus need quarterly distributions of duration rather than maturity. We first divide up securities by maturity and credit quality, and then map maturity to duration.

We begin with the regulatory information on security maturity by risk-type. We treat mortgage-backed securities (MBS) separately from other securities. For MBS, the call reports provide the maturity distribution directly.[29] For all other securities, we assume that maturity and credit quality are independent, and we allocate securities of different credit quality proportionately to all maturity buckets.

[29] We obtain the maturity information from the bank level call reports and aggregate it to the BHC level. Note that the maturity distributions are not only based on fair values but also on book values for held-to-maturity securities. We thus need to assume that the maturity distribution applies to the fair value of total securities.

The reported maturity ranges for securities are the same as for loans (see Figure A.4), starting with one-quarter (i.e., maturity or repricing within a quarter) and going up through maturing or repricing in more than 15 years. As for loans, we assume a maximum maturity of 30 years and map positions from each maturity bucket at time t into a quarterly maturity distribution ranging from one-quarter up to 120 quarters. We allocate positions in the first maturity bucket, maturing within a quarter, to the first maturity quarter. We allocate positions in the second through fourth maturity bucket (three-month through one-year, from one year to three years, and from three to five years) uniformly across all maturity quarters for a given bucket. For example, for the second maturity bucket, we evenly spread one-third of the bucket position at time t across the second, third, and fourth maturity quarters of the maturity distribution.

For the longer maturity buckets (between five and fifteen years, and longer than fifteen years), we assume exponentially decaying weights to not overstate the maturity of securities based on a uniform allocation assumption. Specifically, for positions maturing in more than 5 years and up to 15 years, we choose the weights such that the average maturity of this bucket is roughly 7.5 years compared to 10.125 years implied by the uniform distribution.[30] For the bucket maturing in more than 15 years, we choose the exponential weights such that the average maturity is roughly 18 years rather than 22.625 years.[31] The aggregate effect of this assumption is rather small. The average maturity of the aggregate security portfolio over our sample period is about 6 months lower than that implied by a uniform distribution of maturity-bucket positions across the quarterly maturity distributions.

Equipped with a maturity distribution by credit quality (MBS versus others), we then convert the joint credit-maturity distributions into a joint credit-duration distribution. That is, we convert the security maturity distribution of a given credit quality (say MBS) into their corresponding duration distribution using the appropriate discount rates for each credit category (for example, BBB corporate bond prices for securities in the 100% risk weight category and A corporate bond prices for securities in the 50% risk weight category). Using the bond prices and yields with that credit rating, we compute the duration of this coupon-bond portfolio as

$$d_t^{(m)} = \frac{y_t^{(m)} \cdot \left(\sum_{i=1}^{m} n \cdot P_t^{(n)}\right) + m \cdot P_t^{(m)}}{y_t^{(m)} \cdot \sum_{n=1}^{m} P_t^{(n)} + P_t^{(m)}},$$

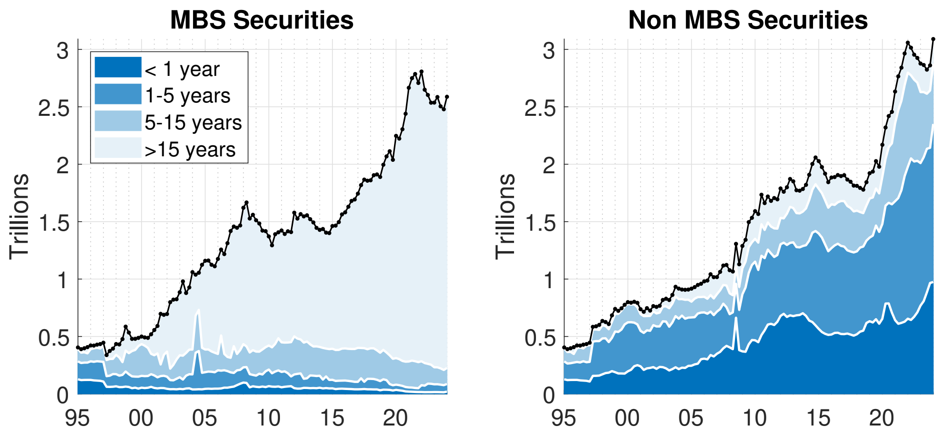
[30] The weight on maturing in 41 quarters is 9.7%, the weight on maturing in 42 quarters is 8.8%, and so on, until the weight on maturing in 60 quarters is 0.2%. The weights map a given maturity-bucket position into the quarterly maturity distribution and add up to one.

[31] Specifically, the weight on maturing in 61 quarters is 9.5%, the weight on the 62 maturity quarter is 8.6% and so on until the weight on maturity quarter 120, which is 0.03%.

where the quarter is t, maturity m, zero-coupon bond price $P_t^{(n)}$ with maturity m and corresponding yield $y_t^{(n)}$ for that credit rating, assuming that the coupon bond trades at par.

We then assign the dollar position in a maturity quarter to the corresponding duration quarter. Figure A.9 presents the distribution of MBS-securities and non-MBS-securities of the aggregate banking sector across duration buckets.

Figure A.9: Security holdings of U.S. banking sector by duration bucket



Notes: This figure shows the loan and security holdings by maturity bucket in trillion dollars. Left panel: market value of MBS securities and trading assets. Right panel: market value of non-MBS securities and trading assets.

B.4 Replicating traditional balance sheet positions

We now describe how we replicate balance sheet positions by credit quality and maturity or duration, given the distributions for loans and securities from Section B.3.

Securities. The representation of securities positions is straightforward once we know each position's duration, credit risk, and fair values. Section B.2 explains how we obtain these data from the regulatory filings. To compute the value of the factor portfolios for a position in some instrument, we multiply the fair value of the position at time t, duration d, and credit rating with the relevant exposures for that instrument, which decomposes the fair value into interest rate risk, credit risk, and cash. For broad classes of fixed-income instruments (such as Treasuries, MBS etc), the resulting factor portfolios then move over time with changes in the composition of maturity and credit rating as described in Sections B.2 and B.3. Since our approach is better suited for fixed-income instruments, we remove the fair value of securities with an equity exposure.[32]

[32]This position is recorded in item bhcka511 until 2017:Q4 and bhckja22 thereafter.

We treat non-derivative trading assets as securities not held for trading.[33] Most trading assets are fixed-income instruments. The trading asset exposure due to equity risk has been separately broken out on the regulatory report since 2008. To get a consistent time series for the pre-2009 period, we use the fact that most equity trading assets are lumped together with "other trading assets" (bhck3541) and remove the associated fair value from the total.

Loans as zero-coupon bond portfolios. Banks report outstanding loan balances in every quarter. To identify factor exposures, we treat these loans as streams of future payments that involve some credit risk of the borrower. To find these payments, we treat all loans as standard installment loans (e.g., a car loan or a mortgage), which feature fixed and equally spaced-out payments to the bank up to the loan's contractual maturity for fixed-rate loans and the loan's next repricing date for floating-rate loans.

We treat each of these future payments as the face value of a zero-coupon bond with the same credit rating. This approach allows us to represent the loan book as a portfolio of zero-coupon bonds. To compute the fair value of the loan portfolio, we multiply each face value by the appropriate zero-coupon bond prices and then sum over all bonds.[34] Factor exposures for each payment—or equivalently each bond in the portfolio—can be read off Figure 2.

When a loan is newly issued, the annuity formula provides the mapping between a loan balance $L^{\text{New}}(t,m)$ and its future (quarterly) constant payment stream:

$$\text{PMT}(t,m) = L^{\text{New}}(t,m) \cdot \frac{y_t^{(m)}}{1 - \frac{1}{\left(1+y_t^{(m)}\right)^m}}, \tag{B-1}$$

where $y_t^{(m)}$ denotes the yield to maturity for a loan with maturity m and the same credit quality. This yield is the rate locked in by this loan until m. Note that "maturity" m corresponds to the contractual loan maturity for fixed-rate loans, and the next repricing date for floating-rate loans. This information is directly provided by the call report data as discussed in Appendix Section B.2 above.

Given a loan's payments PMT per quarter, locked-in rate y, and remaining maturity $n \leq m$,

[33] For securities held for trading, detailed data on maturities is not available. We assume that the average maturity is similar to securities not held for trading. Note that the intended holding period is irrelevant for the market value of a position.

[34] The resulting fair value is not necessarily the market price at which the bank could sell the loan. Indeed, banks might hold loans on their portfolios precisely because the presence of transaction costs or asymmetric information make all or parts of the portfolio hard to sell. At least part of the loan portfolio is thus best viewed as a nontradable "endowment" held by the bank. Nevertheless, our present value calculation shows how the economic value of the endowment moves with interest rates.

we can compute its remaining outstanding balance. The *old* loan's remaining balance at date t is

$$L^{\text{Old}}(t,n) = \frac{\text{PMT}}{y} \cdot \left(1 - \frac{1}{(1+y)^n}\right). \tag{B-2}$$

We use these connections to recursively construct the distribution of remaining future payments and the distribution of remaining loan balances.

For each bank and each credit quality, we compute two matrices. The first matrix contains vintages of payment streams from loans with that credit quality. The matrix has dimensions T, equaling the number of bank observations, and the maximum maturity M of its loans, which we set to 30 years or $M = 120$ quarters. The (t,m) entry of the matrix contains all loan payments the bank expects to receive at $t+m$ for $m = 1,\ldots,M$. We expect payments to occur each quarter up to the loan maturity. The second matrix, with the same dimensions, contains vintages of remaining balances of old loans with the same credit quality. Each entry in row t reflects the remaining loan balances the bank expects to have at $t+m$ for $m = 1,\ldots,M$.

We initialize the algorithm in $t =$1995:Q1 and treat all outstanding loans in this quarter as newly issued. For every maturity $m = 1,\ldots M$ and credit quality, we obtain the outstanding loan balance $L(t,m)$ from a bank's balance sheet data. We further assume that the loan rate $y_t^{(m)}$ is the current yield on a zero-coupon bond of maturity m with the same credit quality. Using the annuity formula (B-1), we compute the payments $\text{PMT}(t,m)$ and allocate them to each future quarter of the payment stream matrix in which they are expected to be made. This means we add the payment to rows $t+j$ for $j = 1,\ldots,m$ in columns 1 through $m-j$. Moving across the maturity distribution, we cumulatively add payments $\text{PMT}(t,n)$ of loans with other maturities n to all entries of the payment matrix in which they are expected to occur.

We also initialize the matrix with the remaining balances of old loans. In the initial quarter $t =$1995:Q1, we compute the remaining loan balances for all future quarters. We apply the formula (B-2) using the locked-in rates $y = y_t^{(m)}$ and the associated payments $\text{PMT}{=}\text{PMT}(t,m)$ given the maturity m of the loan, and compute the remaining balances in all future quarters for elapsed maturity $j = 1,\ldots,m-1$. Starting with the longest remaining maturity, we enter these remaining balances as $L^{\text{Old}}(t+j, m-j)$ in row $t+j$ (e.g., $j = 1$ corresponds to 1995:Q2) up to row $t+m-1$, where the loan has a remaining maturity of one-quarter.

We then move forward to the next quarter $t+1$. We first find the new loans originated in that quarter. For each credit rating, we compute new loan issuance as

$$L^{\text{New}}(t+1,m) = L(t+1,m) - L^{\text{Old}}(t+1,m),$$

where $L(t+1,m)$ is the bank's outstanding loan amount with maturity m of a specific credit quality that we measure in the balance sheet data, and $L^{\text{Old}}(t+1,m)$ denotes the $t+1$ old loan balances with the same maturity and credit quality originated in earlier quarters. Any differences between the reported loan amounts on the balance sheet $L(t+1,m)$ and old balances $L^{\text{Old}}(t+1,m)$ must be due to the removal of old loans or issuance of new loans.[35]

Our algorithm computes the future payments associated with the new vintage of loans with face values $L^{\text{New}}(t+1,m)$ based on the current loan rates $y_{t+1}^{(m)}$. When the face value of new loans is positive, we add these payments to the loan portfolio's future payment streams. When $L^{\text{New}}(t+1,m) < 0$, the bank must have sold or written off more loans than they issued. In this case, we subtract the future payments associated with the canceled old loans and remove them from the loan portfolio's future payment streams. In both cases, we arrive at a new set of payment streams for quarter $t+1$. Before the algorithm moves on to the next quarter, we also update the distribution of old outstanding loans by adding or subtracting the future remaining balances of loans issued in $t+1$, depending on the sign of $L^{\text{New}}(t+1,m)$.

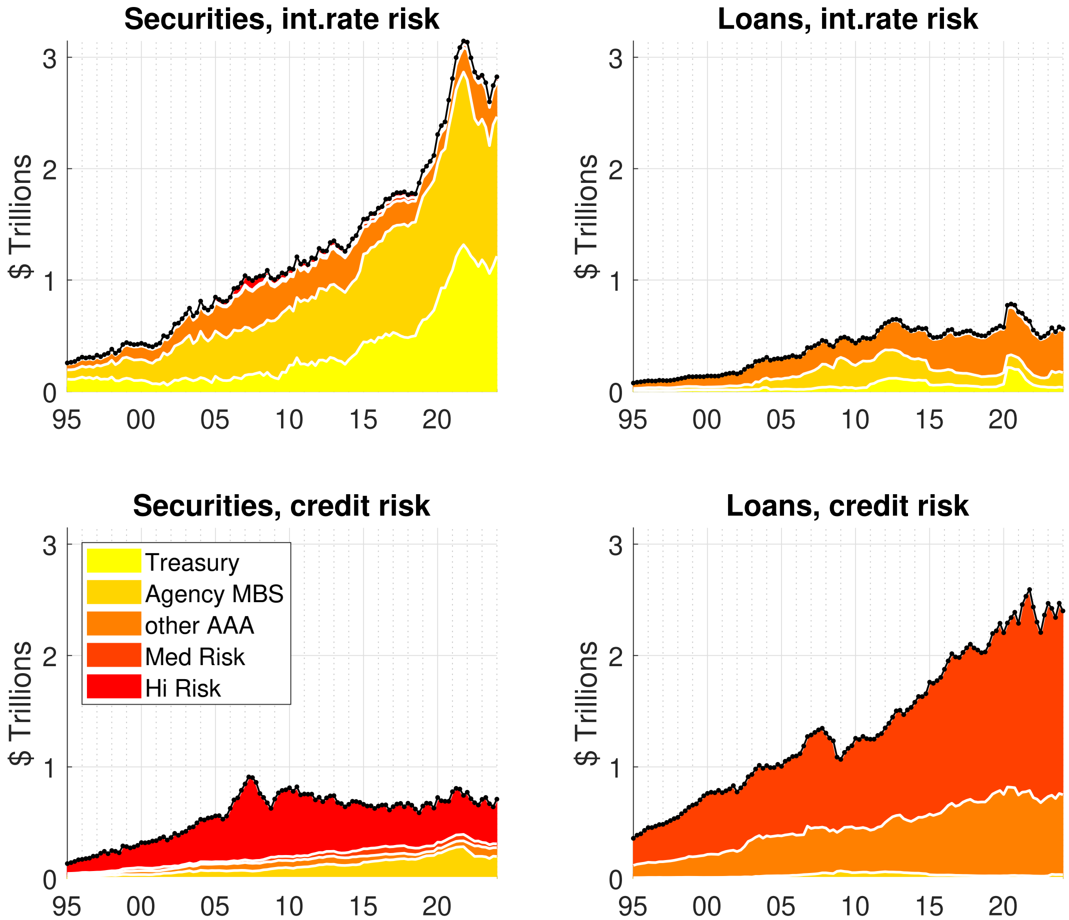
Once we have computed the face values of the zero-coupon bond portfolio that mimic the expected payments associated with the bank's loan portfolio of a particular credit risk, we use the yield curve in quarter t that reflects this credit risk to compute the fair value of the zero-coupon bond face value as of quarter t. We can then multiply these fair values with the respective exposures of zero-coupon bonds, decomposing the fair values into interest rate risk, credit risk, and cash. As a by-product, we obtain an estimate of the loan's fair value by summing the fair values of all promised payments.

Loan and securities risk exposure. We briefly summarize replication results. The left column of Figure A.10 summarizes aggregate exposures of the U.S. banking sector due to securities (including trading securities but excluding equity exposures). The color coding is the same as in the left panel of Figure A.8, which provides the raw data counterpart. The top and bottom panels show interest-rate risk and credit risk exposures. The numbers in the top panels do not add to the total from Figure A.8. A portfolio with the same factor exposure as that held by U.S. banks thus also involves a positive position in cash (or some other instrument uncorrelated with our factors).

Recall that while the loadings on the risk factors (i.e., β_j^i) are constant over time, the risk factors themselves evolve, and their dynamics are allowed to change. As a result, shifts in factor dynamics lead to changes in the risk exposures of a given bank position.

[35]When the bank acquires another bank at date $t+1$, we need to amend this step. We now observe two vintage distributions of loans at date t for the acquirer and the target, which imply two sets of payment streams. We thus construct old loans $L^{\text{Old}}(t+1,m)$ at date $t+1$ by amortizing loans at both acquirer and target by one quarter and taking the sum.

Figure A.10: Risk exposures in securities and loans of U.S. banking sector



Notes: This figure shows the loan and security exposures by interest rate and credit risk. Colors in all panels reflect risk classes indicated in the legend in the bottom left.

Our representation of loans is illustrated in the right column of Figure A.10, which can be compared to the plot of accounting measures in the right panel of Figure A.8. The raw totals drop off to just below $6 trillion in late 2007. Our exposure measures show that credit risk increased by $1 trillion since then. At the same time, exposure to interest-rate risk temporarily declined after the financial crisis. The reason is the negative correlation between risky and riskless bond prices that began in late 2008. We also note that our approach finds a spike in credit risk right before the financial crisis. This spike is visible both for loans and securities. Overall, however, most of the exposure to credit risk on banks' books comes from the loan portfolio.

Balance sheet net cash position, deposits, and long-term debt. We define the net balance sheet cash position as short-term assets minus short-term debts, treating both as cash positions. Short-term assets are cash and balances due from depository institutions, federal funds sold, and securities purchased under the agreement to resell. Short-term debts are non-time deposits and time-deposits maturing within a year, federal funds purchased, and securities sold under agreements to repurchase.

After excluding short equity positions and the negative fair value of trading derivatives, trading liabilities are typically small and treated as short-term riskless debt, maturing within one quarter.[36] We treat long-term time deposit positions as face values of zero-coupon bonds, which we value (i.e., convert to fair values) with the maturity-matched Treasury zero-coupon bond prices. As before, we can read factor exposures off Figure 2.

The remaining financial liabilities of banks include long-term debt (other borrowed money), which is reported at face value. We treat other borrowed money as face values of AAA-rated corporate coupon bonds. We follow a similar procedure for loans by constructing vintages of payments and valuing the resulting payment streams. The difference to loans is that we assume debt is not amortized. Instead, the bank makes coupon payments and pays the face value at maturity. We initialize the algorithm by assuming that all bank debt was newly issued at the beginning of our sample, 1995:Q1. For each face value amount of maturity m, we construct the quarterly coupon payment by first computing each quarterly payment and then allocating the payments across time. We compute the payment simply by multiplying the face value amount with the maturity-matched yield from the current credit-matched yield curve. The m-period ahead payment also includes the face value itself. We keep track of the face value and when the bond matures. Moving to $t + 1$, we compute the newly issued bond face value with maturity m as the difference between the current balance sheet amount of maturity m and the sum of face values of the previously issued bonds with remaining maturity m. Similar to loans, we end up with a distribution of expected payments, which we view as face-values of zero-coupon bonds and map into exposure using replication weights from Figure 2.

C Details on credit-derivatives

This appendix describes the replication of credit derivatives. The main idea is as follows: When a bank purchases a standard credit default swap to protect a credit exposure with rating c and duration d, it effectively buys a default-free bond of duration d and sells a credit-risky bond of rating c and duration d. Since we know the net fair value of that position, we can define the long

[36] We remove short equity positions from trading liabilities to focus on the fixed-income positions of banks. We also removed the equity exposures from trading assets when we computed their fixed-income exposure. We remove the negative fair value of trading derivatives from trading liabilities since our derivative estimation already captured them.

Figure A.11: HC-L Credit Derivative Notional Reporting by Maturity and Rating

Dollar Amounts in Thousands	(Column A) One year or less				(Column B) Over One Year Through Five Years				(Column C) Over Five Years				
	BHCK	Bil	Mil	Thou	BHCK	Bil	Mil	Thou	BHCK	Bil	Mil	Thou	
7. d. Notional amounts by remaining maturity:													
(1) Sold credit protection:													
(a) Investment grade	G406				G407				G408				7.d.(1)(
(b) Subinvestment grade	G409				G410				G411				7.d.(1)(
(2) Purchased credit protection:													
(a) Investment grade	G412				G413				G414				7.d.(2)(
(b) Subinvestment grade	G415				G416				G417				7.d.(2)(

Notes: This figure presents a snapshot of the FR-Y-9C report schedule HC-L (Derivatives and Off Balance-Sheet-Items) item 7d (Notional amounts by remaining maturity and credit rating). This schedule is from the December 2015 report.

default-free bond position as the sum of the net fair value and the fair value of the credit-risky bond. We can then replicate each fair value component separately. We now provide more details.

C.1 Data

We obtain the total notional of credit default derivatives from the "Off-Balance-Sheet Items" schedule of the regulatory filings. Credit-default derivative notionals have been available since 1997:Q1. Until 2005:Q4, the item was bhcka535 for bought protection and bhcka534 for sold protection. Starting in 2006:Q1, the total notional of protection sold is the sum of items bhckc968 (CDS), bhckc970 (total return swaps), bhckc972 (credit options), and bhckc974 (other credit derivatives). For the total notional for the purchased protection, we sum items bhckc969 (CDS), bhckcc971 (total return swaps), bhckc973 (credit options), and bhckc975 (other credit derivatives). Since 2009, the reports distinguish between total notionals sold and purchased by maturity bucket (one year or less, one to five years, and over five years) and credit rating (investment grade and subinvestment grade). Figure A.11 shows the item definitions for the joint credit and maturity distribution of credit notionals.

The associated fair values have been available since 2002:Q1. We obtain the gross fair values (positive and negative) for sold protection (bhckc219 and bhckc220) and bought protection (bhckC221 and bhckC222). We compute the net fair value for sold (bought) protection as the difference between bhckc219 and bhckc220 (bhckc221 and bhckc222). The fair value data availability for credit derivatives means that the earliest start date for the credit derivative replication is 2002:Q1.

C.2 Credit and maturity distribution

We map the joint credit and maturity distributions into quarterly maturity distributions by credit quality. Credit derivative notionals are reported as investment grade or subinvestment grade. We define investment grade as A-rated credit quality and subinvestment grade as B-rated credit quality. Within each maturity bucket, we assume a uniform distribution of the notionals across maturity quarters and a maximum maturity of 6 years.[37] For each credit rating, we then map each credit quality's maturity distribution into a distribution of durations using yields from investment grade (A-rated) and subinvestment grade (B-rated) bonds, respectively. We do this separately for purchased protection and sold protection.

While fair values have been available since 2002:Q1 and notionals since 1997:Q1, the maturity distributions have been only available since 2009:Q1. To deal with the missing maturity information from 2002:Q1 through 2008:Q4, we assume that it equals the average maturity distribution over the available sample from 2009:Q1 through 2024:Q1.

We further assume that the distribution of notionals across credit quality and duration also applies to the distribution of net fair values across credit quality and duration.

C.3 Replication of credit derivatives

We replicate credit derivatives as if all were credit default swaps. This is a simplifying assumption but captures the vast majority of credit derivatives. On average, between 2006:Q1 and 2024:Q1, where we have data on the type of credit derivatives, 93% of credit derivatives of the aggregate banking sector are credit default swaps.

When a bank buys a credit default swap with credit quality c and duration d, it essentially swaps out a credit-risky bond with quality c and duration d against a default-free swap-quality bond with duration d. Thus, the fair value of a position in a purchased credit default swap $F_t^{\text{cds}}(d,c)$ can be represented as the difference between the default-free bond's fair value $F_t^{\text{free}}(d)$ and the credit-risky bond's fair value $F_t^{\text{risky}}(d,c)$:

$$F_t^{\text{cds}}(d,c) = F_t^{\text{free}}(d) - F_t^{\text{risky}}(d,c).$$

We compute the risky bond's fair values as $F_t^{\text{risky}}(d,c) = N_t(c,d) \times P_t(c,d)$, where $N_t(c,d)$

[37] Specifically, we distribute the notionals of the first maturity bucket (less than one year) uniformly across the first four quarters, the second maturity bucket (over one year up to five years) uniformly across the 16 maturity quarters spanning one year plus one quarter up to five years (quarter 20), and the last maturity bucket (more than five years) across the four quarters from year five plus one quarter (quarter 21) up to year 6 (quarter 24).

denotes the notional of credit derivatives with credit quality c (either A or B rated) and duration d, as given by the data, and $P_t(c, d)$ is the appropriate bond price for the same credit quality and duration. We then find the fair value of the default-free bond position as

$$F_t^{\text{free}}(d) = F_t^{\text{cds}}(d, c) + N_t(c, d) \times P_t(c, d).$$

When a bank sells credit-default swap protection, it essentially goes long a credit-risky bond and shorts a default-free bond. Its fair value is minus the fair value of the corresponding long CDS position

$$-F_t^{\text{cds}}(d, c) = F_t^{\text{risky}}(d, c) - F_t^{\text{free}}(d).$$

Hence, we can again find the fair value of the default-free bond from the fair values of the short CDS position and the credit-risky bond.

Our replication procedure then takes the distribution of fair values by credit quality, duration, and trading direction and then proceeds as we have done throughout this paper, i.e., using the replication weights to split up each fair value position into an interest rate risk, a credit risk, and a remaining cash position.

D Details on interest-rate derivatives

This appendix describes how we estimate risk exposures through interest-rate derivatives. The basic idea is that any such derivative can be represented as a portfolio that contains only the default-free spanning bond and cash. Moreover, the comovement of changes in fair value with bond-price changes reveals latent exposure to long bonds. The system (3) described in the main body of the paper formalizes this idea. The estimation uses a closely related system, using a convenient change of variable.

The appendix is structured as follows. Section D.1 describes the available data. Section D.2 explains how we correct fair values of swaps for gains from intermediation. Section D.3 then explains how we map derivatives to factor portfolios and how changes in fair values relate to changes in bond prices and bank trading of exposure. In particular, it derives the system (3). Section D.4 describes the estimation strategy and discusses the identifying assumptions. Section D.5 presents estimation results. The estimation is performed using data for each bank individually for the entire sample. As in the main body of the paper, we use Bank of America as a leading example to illustrate our approach.

D.1 Data

We use data on positions from Schedule HC-L, Derivatives and Off-Balance-Sheet Positions, and data on maturities from Schedule HC-R, Regulatory Capital. Schedule HC-L reports notionals and the sums of all contracts with positive and negative gross fair values, broken down by types of exposure, in particular distinguishing interest-rate derivatives from equity, forex, credit, and commodity contracts. Interest-rate derivatives constitute the overwhelming share of all derivative contracts with nearly 80% share of total notionals. Schedule HC-L further distinguishes derivatives by whether or not they are held for trading. Derivatives for trading tend to be especially large for the major dealer banks.[38] Finally, notionals are broken down by swaps, forwards, futures, and options. On average, over our sample, swaps, forwards, and futures are the vast majority of notionals, while only 20% of notionals are options.

We consider the "for trading" position separately from the "not for trading" position. Since the parameters of our estimation capture in part the bank's trading strategy, running two estimations allows for potentially different strategies underlying the two positions. For example, we define N_t as the sum of all notionals of interest-rate contracts for trading purposes (BHCKA126). Our replicating procedure of trading derivatives considers the overall net fair value of interest-rate contracts, that is the sum of all interest-rate contracts with positive fair value (item BHCK8733) less those with negative fair value (BHCK8737). This netting is important to account for many offsetting exposures that market makers take.

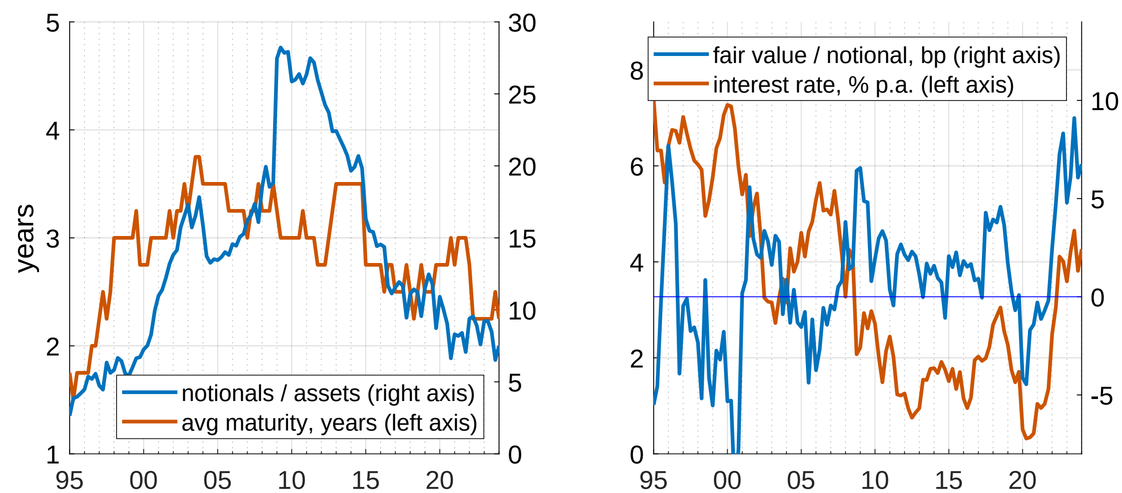
Schedule HC-R also provides the shares of notionals of all interest rate derivatives with remaining maturity of less than one year (BHCKS582 + BHCKS603), 1 to 5 years (BHCKS583 + BHCKS604) and more than 5 years (BHCKS584 + BHCKS605). Our estimation requires an estimate of duration d_t of the derivatives, for which we use the notionals-weighted average duration, assuming that durations within maturity buckets are 6 months, 3 years, and 8 years, respectively. Average durations are typically below 5 years, and our results are not particularly sensitive to the precise number. Since we do not observe maturity separately for for-trading and not-for-trading positions, we use the same average in both estimations.

Figure A.12 displays the observables of Bank of America's for-trading portfolio. The left panel shows notionals relative to assets (measured along the right vertical axis) together with the notional-weighted average maturity (measured along the left vertical axis). The right panel shows

[38] Formally, the designation "for trading" only determines whether marked-to-market gains and losses are reported in income or OCI. Guidance on designation suggests that "for trading" contracts are held for shorter periods but does not restrict the purpose of the contract. In particular, this label does not allow inference on whether the contract is used for hedging or speculation.

the fair value per unit of notional in basis points (right axis) together with the interest rate on the spanning bond (left axis). Since BofA is a major dealer with many offsetting positions, its notionals are many times larger than assets, while the fair value is a tiny share of notionals.[39] Notionals mostly move gradually but can also have sizeable jumps, for example, when BofA acquired Merrill Lynch in early 2009. Maturity is quite stable; it tends to shorten when interest rates rise.

Figure A.12: Bank of America's for-trading derivatives portfolio

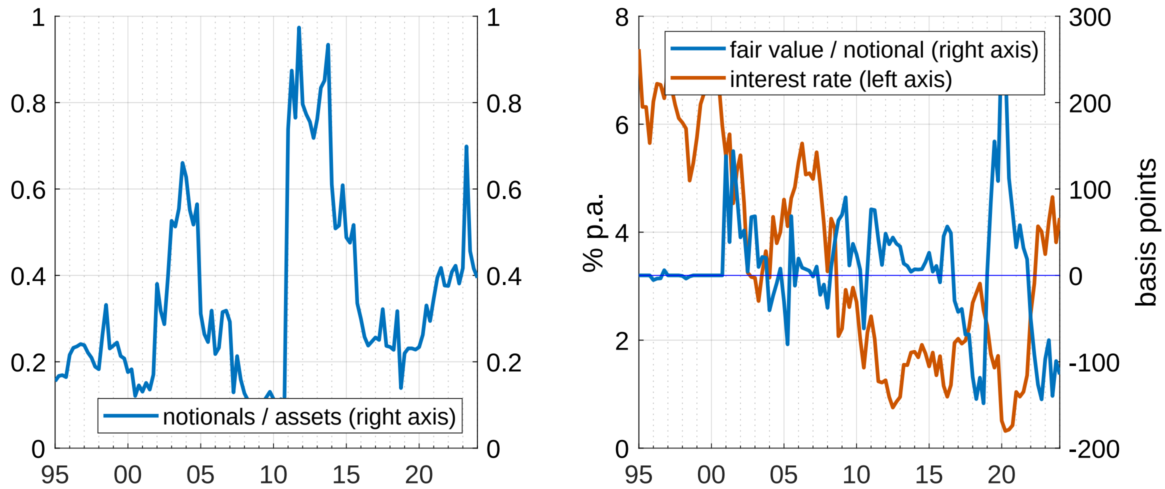


Notes: Left panel shows total for-trading notionals of interest rate risk derivatives as a share of assets (blue) and average maturity (orange). Right panel shows fair value of for-trading interest-rate derivatives relative to notionals (blue) and 5-year swap-quality interest rate (orange).

Figure A.13 displays the observables of Bank of America's not-for-trading portfolio. The first striking difference is that these notionals are much smaller, now a share of assets rather than a large multiple. At the same time, notionals exhibit much larger jumps, sometimes by more than 100%. This feature is typical of not-for-trading portfolios. For smaller banks, we often see the beginning of a derivatives program where notionals jump from zero to some positive amount of notionals that then stays unchanged for some time. The smaller scale of notionals implies that the ratio of fair value to notionals is now larger, on the order of a few percentage points.

[39]Before the financial crisis, most intermediation in the swap market did not go through a clearinghouse but instead involved large bilateral interdealer positions. Individual dealers thus held large offsetting pay-fixed and pay-floating positions due to intermediation between clients and/or other dealers. The increasing importance of swap clearing has reduced outstanding notionals.

Figure A.13: Bank of America's not-for-trading derivatives portfolio



Notes: Left panel shows total not-for-trading notionals of interest rate risk derivatives as a share of assets (blue). Right panel shows fair value of for-trading interest rate risk derivatives relative to notionals (blue) and 5-year swap-quality interest rate (orange).

D.2 Correcting fair values for swap intermediation

Our strategy throughout the paper is to state positions at market value, leaving out compensation for intermediation or rents incorporated into prices. In the case of swaps, dealer banks make money by charging bid-ask spreads incorporated into swap rates. Moreover, a dealer intermediating between two counterparties often enters offsetting positions with each party. This practice—most prominent before the financial crisis when swap clearing was rare—contributes to very large notionals at the major dealer banks. It also implies that for-trading fair values contain the present value of future bid-ask spreads. We want to subtract those present values from fair values.

In a textbook frictionless market, swap rates are determined at inception such that their initial fair value is zero. In practice, the swap rate on a pay-fixed (pay-floating) swap is typically lower (higher) than the rate that makes the fair value zero. Dealers intermediate between two clients that want, say, a pay-fixed and a pay-floating swap of the same maturity, respectively, by entering pay-floating and pay-fixed swaps, respectively, with those clients. As a result, the for-trading portfolio of major dealer banks contains large offsetting positions with positive and negative fair values on which the dealers earn bid-ask spreads. For Bank of America, the total positive (negative) fair value positions are, on average, 21.0% (20.6%) of assets, both much larger than net fair value positions, which are, on average, .04% of assets.

Consider a bank that has assembled a portfolio of swap contracts at date t, represented by a set of indices J_t. An individual contract $j \in J_t$ is identified by its notional value N_j, its remaining maturity m_j, its swap rate s_j, and by whether the bank pays a floating ($\sigma_j = 1$) or a fixed interest rate ($\sigma_j = -1$). Let $N_t = \sum_{j \in J_t} N_j$ denote total notionals at date t. Let $P_t^{(n)}$ denote the price of an n-period zero coupon bond from the swap curve. The fair value of the swap portfolio is the difference between the values of all fixed and all floating legs

$$F_t N_t = \sum_{j \in J_t} N_j \sigma_j \left(\sum_{i=1}^{m_j} s_j P_t^{(i)} + P_t^{(m_j)} \right) - \sum_{j \in J_t} N_j \sigma_j, \tag{D-3}$$

which defines F_t as the fair value per dollar notional.

We assume that the initial rate on any swap contract j of direction σ_j (where $\sigma_j = 1$ means pay-floating) takes the form $s_j = \bar{s}_j - \sigma_j b_j/2$, where $\bar{s}_j$ is the rate that sets fair value to zero and b_j is a bid-ask spread. Following standard terminology, we refer to $\bar{s}_j$ as the "mid-market rate" that sits halfway between the bid and ask rates. A bank that intermediates a swap between two clients takes on both a pay-fixed and a pay-floating position and earns a bid-ask spread every period. When banks mark swaps to market, they thus include the present value of rents. Banks report the fair value

$$F_t N_t = \frac{1}{2} \sum_{j \in J_t} N_j b_j \sum_{i=1}^{m_j} P_t^{(i)} + FV_t, \tag{D-4}$$

which contains two components. The first component is the present value of bid-ask spread income earned on all contracts. The second component is the fair value at mid-market rates, and hence "cleaned" of compensation for market making, which we use as our key observable.

We obtain a time series of average bid-ask spreads on new swaps by maturity from Bloomberg. We use this time series together with the bank's series of notionals to construct an estimate, at every date, of the bank's path of average *future* bid-ask spreads. In particular, we assume that in the first sample period ($t = 0$), all swaps are new, and we record the stream of bid-ask spread payments $\{b_j\}_{j \in J_0}$ on those swaps. We then proceed recursively: for each period t and maturity, new swaps are defined as the difference between total notionals in period t and "old" notionals that remain from period $t-1$, taking into account that the old swaps have aged by one period. We then apply the current bid-ask spreads $\{b_j\}_{j \in J_t}$ to the new swaps and thereby add to the stream of payments for all future periods.

We assume that spreads are earned only on intermediation between non-bank clients, whereas the interdealer market is competitive. To assess the share of positions intermediated between clients, we use data on net credit exposure in derivatives broken down by broad counterparty category, available in the call reports since 2009. We use the 2009 share to fill in earlier periods.

We can thus divide notionals outstanding at date into two groups: those with bank and non-bank counterparties. We set spreads on notionals with bank counterparties to zero and use average spreads on the others.

The spread series for the typical maturity declines over time. Before 2006, the spread series is often at .5bp, with occasional spikes down to .1bp, whereas after the financial crisis it often sits at .1bp with occasional spikes up. The resulting compensation and hence its present value can still be significant since the small spread multiples large notionals. For BofA, we obtain a present value of spread income of 3-4% of positive net fair value and up to .6% of assets before the financial crisis. Our correction matters since net fair values are a small share of assets. At the same time, the present value of spread income is stable relative to net fair value and does not alter the comovement of net fair value with returns. The correction we do therefore has some effect on the magnitude of exposures, but little effect on signs and dynamics. Moreover, any exposure from future spreads must be small relative to the exposure from fixed legs, since it is a claim to a small share of interest payments.

D.3 The evolution of fair value and exposure

We now derive a parsimonious description of how the fair value of an interest-rate derivatives portfolio comoves with the portfolio's interest-rate risk exposure, summarized by equation (3) in the main body of the paper. A reformulation of this system then leads to the econometric model we estimate.

Our starting point is that any interest-rate derivatives portfolio can be replicated by a position in the swap-quality default-free spanning bond and cash. Consider a portfolio that is equivalent, per unit of notional, to θ_t units of the spanning bond and k_t dollars in cash. When the price of the spanning bond is P_t, the fair value of the portfolio is

$$F_t N_t = P_t \theta_t N_t + k_t N_t \tag{D-5}$$

and the exposure of the portfolio per unit of notional is $x_t = P_t \theta_t$.

Bank trades and price changes. Between dates t and $t+1$, banks can trade in derivatives. This trading effectively changes the number of bonds or the amount of dollars in cash in their derivatives portfolio. Moreover, the bond price at $t+1$ can differ from that at t.

At date t, the bank records notionals N_t and fair value $F_t N_t$. We decompose the change in the portfolio into two pieces: changes due to the cancellation of existing contracts and the inception of new contracts. Using hats for canceled positions (and notionals) and stars for incepted positions at time t, we write the new number of bonds and amount of cash as

$$\begin{aligned}\theta_{t+1}N_{t+1} &= \theta_t N_t - \hat{\theta}_t \hat{N}_t + N_t^* \theta_t^*, \\ k_{t+1}N_{t+1} &= k_t N_t - \hat{k}_t \hat{N}_t + k_t^* N_t^*,\end{aligned} \tag{D-6}$$

We also write $\hat{F}_t$ and F_t^* for the net fair values of canceled and incepted contracts at date t prices, respectively.

We can then write the date $t+1$ fair value as

$$\begin{aligned}F_{t+1}N_{t+1} &= \theta_{t+1}P_{t+1}N_{t+1} + k_{t+1}N_{t+1} - \theta_{t+1}P_t N_{t+1} + \theta_{t+1}P_t N_{t+1} \\ &= \theta_{t+1}(P_{t+1} - P_t)N_{t+1} + k_{t+1}N_{t+1} + \theta_{t+1}P_t N_{t+1} \\ &= \theta_{t+1}(P_{t+1} - P_t)N_{t+1} + k_t N_t - \hat{k}_t \hat{N}_t + k_t^* N_t^* + (\theta_t N_t - \hat{\theta}_t \hat{N}_t + \theta_t^* N_t^*)P_t \\ &= \theta_{t+1}(P_{t+1} - P_t)N_{t+1} + (P_t\theta_t + k_t)N_t - (P_t\hat{\theta}_t + \hat{k}_t)\hat{N}_t + (P_t\theta_t^* + k_t^*)N_t^* \\ &= x_{t+1}\frac{P_{t+1} - P_t}{P_{t+1}}N_{t+1} + F_t N_t + F_t^* N_t^* - \hat{F}_t \hat{N}_t. \end{aligned} \tag{D-7}$$

Here the first equality adds and subtracts the same term at the end. The second equality rearranges to obtain a first term that captures the effect of price change, and the third substitutes for cash and bond positions from (D-6). The fourth equality rearranges by grouping bond and cash positions according to whether they were already present at t, canceled (with hats) or newly incepted (starred), and the fifth applies definitions of fair values.

The first equation of our main system (3) in the body of the paper is a rewriting of (D-7) using the definition

$$\varepsilon_{t+1} := F_t^* \frac{N_t^*}{N_t} - \hat{F}_t \frac{\hat{N}_t}{N_t}. \tag{D-8}$$

Mechanically, the variable ε_{t+1} describes what the change in fair value between t and $t+1$ would have been if the price of the spanning bond had remained constant. Economically, it captures adjustments the bank makes by either canceling or incepting new contracts. We note that for swaps and forwards, the fair value at inception is always zero so $F_t^* = 0$ and ε_{t+1} only reflects cancellation of contracts that were already on the books at date t.

Duration and net short notionals. The accounting identity (D-8) relates only fair values, notionals, and exposure. In order to bring in information on duration, it is helpful to first define *net short notionals*, a 1-1 translation of exposure that measures how levered the derivatives position is. We then show that net short notionals are also convenient to use as latent state variable for estimation.

To elaborate, any interest-rate derivative is equivalent to a long-short portfolio that takes a (long or short) position in the swap-quality default-free spanning bond as well as an opposite (short or long) position in cash, respectively. For example, the fixed leg of a swap is a long position in the spanning bond, whereas the floating leg is a cash position. A portfolio of interest-rate derivatives thus sums over many bond and cash positions to arrive at an aggregate bond position of duration d_t, say, and an aggregate cash position. We refer to the value of this cash position as a share of total notionals as the bank's share of *net short notionals*, denoted by ϕ_t. It summarizes the cash position (either short or long) while holding duration fixed: higher $|\phi_t|$ means that the bank has a higher cash position opposite its bond position.

Since we replicate positions with spanning bonds of a specific duration n that may differ from the duration of the bank's portfolio d_t, the overall cash position in our replicating portfolio is not the same as net short notionals ϕ_t. This is because cash not only represents the opposite ϕ_t of the bond position, but it also helps in replicating the correct duration of the bond position. In general, the portfolio per unit of notional thus has the representation

$$F_t = x_t + c_t - \phi_t \,, \tag{D-9}$$

where c_t is cash that helps replicate the bond position with duration d_t. The value of the bond position (such as the value of the fixed leg in the case of a swap) is $F_t + \phi_t$.

In general, all three elements x_t, c_t and ϕ_t can be positive or negative and need not be otherwise related except in special cases. As an example, when the bank enters a single pay-floating swap, we have $\phi_t = 1$ and $x_t > 0$. The sign of the cash position c_t depends on the duration d_t of the fixed leg. If its duration is longer than the maturity of the spanning bond, $d_t > n$, the cash position is negative $c_t < 0$. In this case, the fixed leg is a leveraged position in the spanning bond that is more exposed to interest rate risk than the spanning bond itself. In contrast, when $d_t < n$, the cash position is positive, $c_t > 0$, and the fixed leg is safer than the spanning bond. For a single pay-fixed contract, we have by analogy $\phi_t = -1$ and $x_t < 0$, and the sign of c_t again depends on duration. More generally, a swap portfolio can include partially offsetting positions with different maturities and swap rates. In this case, simple relationships do not apply.

We can distinguish the two cash positions ϕ_t and c_t when we observe the average duration d_t of the derivatives portfolio, which corresponds to the duration of its bond position, worth $F_t + \phi_t = x_t + c_t$. The spanning bond has duration n, while cash has a short (one period) duration. The standard definition of duration implies

$$d_t = \frac{n x_t + c_t}{x_t + c_t} = \frac{n x_t + \phi_t + F_t - x_t}{x_t + \phi_t + F_t - x_t} = \frac{(n-1)\, x_t + \phi_t + F_t}{\phi_t + F_t}.$$

Here the second equality follows by solving (D-9) for c_t and substituting.

Rearranging, we obtain a one-to-one relationship between net short notionals and exposure, conditional on the observable fair value F_t and average duration d_t:

$$\phi_t = \frac{n-1}{d_t - 1} x_t - F_t. \tag{D-10}$$

We can therefore formulate the dynamics of risk taking by specifying an evolution equation for either variable, net short notionals ϕ_t or exposure x_t. The system (3) in the main body of the paper describes the joint dynamics of fair value and exposure x_t. It is helpful for interpretation since exposure is our ultimate object of interest, comparable to exposures from other instruments. For estimation, however, it is more convenient to rewrite the system in terms of fair value and net short notionals ϕ_t.

We write the evolution of net short notionals as

$$\phi_{t+1} = \phi_t + u_{t+1}. \tag{D-11}$$

In other words, we define the trade u_{t+1} as the change in net short notionals. As with the definition of ε_{t+1} in (D-8) above, this is without loss of generality until we make a distributional assumption on these trades, which we discuss below. The evolution of exposure, that is, the second equation in (3), is a rewriting of (D-11) that follows from substituting for ϕ_{t+1} using (D-10).

We note that the trade u_{t+1} is a portfolio shift that changes the riskiness of the bank and is, therefore, conceptually different from the trade ε_{t+1} that changes the scale of the portfolio. Of course, some portfolio adjustments may jointly affect u_{t+1} and ε_{t+1}. For example, suppose a bank initially has two positions with the same notionals in pay-fixed and pay-floating swaps, so $\phi_t = 0$. If the bank cancels the pay-fixed swap, net short notionals increase: $\phi_{t+1} = u_{t+1} = 1$. The cancellation further implies that ε_{t+1} equals the date t fair value of the pay-fixed swap, which could be positive, negative, or zero, depending on how market prices moved since the inception of that swap.

To obtain an observation equation to go along with the state equation (D-11), we rewrite fair values (D-7) by substituting net short notionals ϕ_{t+1} for exposure x_{t+1} using (D-10). Dividing by N_{t+1} and using the definition of ε_{t+1} in (D-8), we arrive at fair values per dollar notional

$$F_{t+1} = (F_{t+1} + \phi_{t+1}) \frac{d_{t+1} - 1}{n-1} \frac{P_{t+1} - P_t}{P_{t+1}} + F_t \frac{N_t}{N_{t+1}} + \frac{N_t}{N_{t+1}} \varepsilon_{t+1} \tag{D-12}$$

Equations (D-11) and (D-12) describe the joint dynamics of net short notionals and fair values conditional on prices and notionals, with bank trading summarized by sequences ε_{t+1} and u_{t+1}.

D.4 Estimation strategy

To represent the dynamics more concisely, we introduce two more pieces of notation. First, we define the *gain* on the bond position in the derivatives portfolio

$$R_{t+1} := \frac{d_{t+1} - 1}{n - 1} \frac{P_{t+1} - P_t}{P_{t+1}}. \tag{D-13}$$

The gain moves with the change in the spanning bond price, and more so if the duration of the bond position is longer. While it is not literally a return, it behaves much like a return when n is large, as in our context with $n = 20$ quarters.[40]

Second, we collect all observable variables on the right-hand side of (D-12) and define the adjusted change in fair value per dollar notional N_{t+1} as

$$\Delta\tilde{F}_{t+1} := \Delta F_{t+1} - F_{t+1}R_{t+1} + F_t \frac{\Delta N_{t+1}}{N_{t+1}}. \tag{D-14}$$

The adjustment involves terms that are typically products of two small numbers and hence an order of magnitude smaller than the change in fair value ΔF_{t+1} itself. For BofA, for example, the magnitudes of F_t and the growth rate of notionals can be read off the right panel of Figure A.12.

Our econometric model for the adjusted fair value $\Delta\tilde{F}_t$ and the latent state variable net short notionals ϕ_t is derived from (D-11) and (D-12). We specify

$$\begin{aligned} \Delta\tilde{F}_{t+1} &= \phi_{t+1}R_{t+1} + \frac{N_t}{N_{t+1}}\varepsilon_{t+1}, \\ \phi_{t+1} &= \phi_t + u_{t+1}, \end{aligned} \tag{D-15}$$

where the innovations u_{t+1} and ε_{t+1} are iid and mutually uncorrelated. The observable sequences R_{t+1} and N_{t+1} are exogenous.

Our assumption of independent and iid trades u_{t+1} and ε_{t+1} imposes no a priori structure on the bank's trading strategy. We observe relatively short samples generated by bank trading strategies that reflect many time-varying bank-specific forces, including regulatory compliance, the need to hedge positions, traders' beliefs, and clients' demand for intermediation. We therefore want to allow for flexible movement in trades, as opposed to, say, imposing mean reversion in positions or a systematic response to interest rates that is uniform over time. We note that we do

[40]The return on an n-period zero coupon bond between dates t and $t+1$ is $(P_{t+1}^{(n-1)} - P_t^{(n)})/P_t^{(n)}$. The gain differs from the return on the spanning pond with $n = 20$ because the first price in the numerator and the price in the denominator is $P_{t+1}^{(n)}$. However, when n is large and the period length is a quarter, bonds of maturity n and $n-1$ move closely together, so it matters little which one enters the numerator. Moreover dividing by $P_{t+1}^{(n)}$ rather than $P_t^{(n)}$ amounts to multiplying the return by one plus a small decimal number.

not require that position changes are uncorrelated with gains R_{t+1} in sample, since the observable R_{t+1} is exogenous to the system.

To estimate the state-space system (D-15), we assume that the innovation is normally distributed, $\varepsilon_{t+1} \sim N(0, \sigma_\varepsilon^2)$, and that ϕ_t is a discrete Markov chain. The transition matrix of the Markov chain is constructed by discretizing a random walk with innovations $u_{t+1} \sim N(0, \sigma_u^2)$ truncated at -1 and 1. We estimate the two variances σ_ε^2 and σ_u^2 as well as the initial condition for the latent state variable ϕ_0. We then obtain estimates for the entire path ϕ_t using the optimal smoother implied by our discrete state space model. We use a Monte Carlo approach to take into account the effect of parameter uncertainty on confidence intervals for ϕ and other statistics. We now describe the details in turn.

Cleaning outliers. We perform a number of additional steps to eliminate the impact of measurement error. We measure the fair value per dollar notational F_t for every BHC and calculate the empirical standard deviation of its growth rate in the time series. We then search for dates such that the growth rate is higher than three standard deviations in two consecutive periods (both between periods $t-1$ and t and periods t and $t+1$.) For these "spike" dates, we interpolate fair value as the midpoint between values at dates $t-1$ and $t+1$, thus eliminating the spike. In addition, we search for dates such that notionals are positive at only one date t, with zeros at date $t-1$ and $t+1$. This sometimes occurs for small banks. Since our code makes inference from growth rates, it cannot handle such dates, and we set notionals to zero.

Sample splits. We divide the sample into *spells* of broadly similar derivatives activity and perform a separate estimation for each spell. The motivation is twofold. First, banks sometimes experience large jumps in notionals due to mergers. It is plausible that trading strategy changes, for example, when acquiring another bank that does more business in making markets. Second, small banks sometimes display multiple short episodes of positive notionals, with pauses involving zero notionals in between. This pattern plausibly reflects derivatives programs done for different purposes.

Concretely, a new spell begins at date t if either (i) a merger has occurred at date $t-1$ that increased notionals by more than 20% or (ii) notionals were zero at $t-1$ and are positive at t. A spell ends at date $t-1$ if either (i) occurs or (iii) the bank has positive notionals at $t-1$ and no notionals at t. A typical large bank that expands gradually has a single spell. A typical small bank has, at most, a handful of spells.

For every spell of length T, say, we first collect the exogenous variables R_{t+1} and N_t/N_{t+1} for $t = \{1, \ldots, T\}$. We parametrize the likelihood of the data $\Delta\tilde{F}_{t+1}$ conditional on the exogenous variables by the vector $(\phi_0, \sigma_u, \sigma_\varepsilon)$. Here ϕ_0 is the initial condition for the hidden state ϕ_t, while

σ_ε is the volatility of a normal shock with mean zero. The volatility σ_u regulates the movements of the hidden state. We assume that ϕ_t is a finite state Markov chain that lives on a finite grid $\left\{\bar{\phi}_1, .., \bar{\phi}_N\right\}$ with lowest grid value $\bar{\phi}_1 = -1$ and highest grid value $\bar{\phi}_N = 1$. To construct its transition matrix $\Pi(\sigma_u)$, we first form, for every grid point $\bar{\phi}_j$, a normal pdf with mean $\bar{\phi}_j$ and volatility σ_u. We then find the conditional probability $\Pr\left(\bar{\phi}_i|\bar{\phi}_j\right)$ by integrating over all points on the real line that are closest to $\bar{\phi}_i$. In particular, the boundary points $\bar{\phi}_1$ and $\bar{\phi}_N$ absorb all mass of the pdf outside the grid.

Building the likelihood. We find parameters for every spell by maximizing the likelihood of the data over the spell sample. Building the likelihood from one-step-ahead conditional probabilities involves filtering the hidden state ϕ_t. With our discretization, the usual Kalman filter and smoother are not applicable. However, with a finite grid, we can apply Bayes' rule directly to find posterior probabilities for the hidden state given past data. Similarly, Bayes' rule delivers the conditional probabilities of the data given the entire sample, the finite-state analogue of the Kalman smoother. We use grids with 200 points spread over the interval $[-1, 1]$ with tighter spacing in the middle. Experimentation with finer grids shows that results do not change. We compute standard errors by Monte Carlo simulation. We draw 1,000 samples at the point estimates and re-estimate for every simulated sample. The results deliver confidence intervals for the parameters of each spell and the sequence of hidden states.

D.5 Estimation results

We run the estimation for both for-trading and not-for-trading portfolios of all public banks with such portfolios. We now describe the main properties of the procedure first for the leading example of Bank of America (BofA), then more broadly for the universe of banks.

Results for BofA. Table A.2 reports parameter estimates for both for-trading and not-for-trading positions of BofA. There are two spells in both cases, before and after the Bank of America Corporation emerged from the acquisition of Bank of America (founded in San Francisco as Bank of Italy) by NationsBank in 1998. Since the first spell is very short, its parameters are estimated imprecisely. The same applies to the initial state in the second spell, the net pay-floating notional in 1998. As Figure 3 shows, we cannot be very confident about the sign of the position before 1998. For the second spell with data for trading, however, the code estimates small volatilities both for the innovation in net pay-floating nationals σ_u and the error σ_ε.

To put the numbers in perspective, consider first the magnitude of fair value for trading. Start from the example of a bank that holds a single swap contract, say a 5-year pay-floating swap,

Table A.2: Parameter estimates for BofA derivatives

	for trading				not for trading			
	1995:Q1-1998:Q2		1998Q3-2024:Q1		1995:Q1-1998:Q2		1998Q3-2024:Q1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ϕ_0 (%)	-1.27	(80.43)	0.68	(350.24)	50.00	(276.39)	-800.00	(151.66)
σ_ε (bp)	3.28	(0.64)	1.84	(0.21)	4.29	(0.86)	64.24	(5.15)
σ_u (bp)	1.00	(3.99)	11.26	(7.34)	0.05	(44.02)	161.72	(48.23)

Notes: Parameter estimates based on for trading (left panel) and not-for-trading (right panel) positions of BofA. 1st spell estimated parameters for initial share of net short notionals ϕ_0, and standard deviations of innovations to net short notionals σ_u and error σ_e for two spells 1995-1998Q4 CHECK Standard errors in parentheses.

so $\phi_t = 1$. The banks' exposure is the same as the exposure of the fixed leg, which looks like a bond. A one-percent increase in the 5-year interest rate would lower the price P_t by five percent, and hence decrease fair value by five percent of notionals. The fair-value changes in Figure 3, however, are much smaller, on the order of basis points. As we have discussed, the reason is that Bank of America is a major dealer in swaps, and holds many offsetting positions in pay-fixed and pay-floating swaps. Total notionals in the denominator are therefore much larger.

Our estimated volatilities are then also on the order of basis points. In the typical period, net notionals move between -120bp and $+50$bp of total notionals. Its innovations have an estimated 10bp volatility. The contribution of gains $\phi_{t+1}R_{t+1}$ to fair-value changes is much smaller, as net notionals are multiplied by gains, another small decimal number. The contribution of gains is thus similar in magnitude to that of the errors ε_{t+1}; we have $var(\phi_{t+1}R_{t+1})/var(\Delta\tilde{F}_{t+1})$= 24%. Moreover, the correlation between fair-value changes and the contribution of gains is large at 57%.

Estimating the not-for-trading portfolio also finds a small volatility of innovations to net notionals σ_u, but now a larger error volatility σ_ε. Figure A.13 shows that this estimation works with much larger jumps in notionals. Scaled errors thus account for a larger share of the variation in fair value. As a result, the relative variance of the contribution of gains to fair-value changes is only 4%. Nevertheless, the systematic comovement of fair values and interest rates visible in the right panel of Figure A.13 explains why we infer a position that is most often short interest-rate risk.

Estimates for other banks. Table A.3 provides an overview of the estimations we have run for all the other banks in the sample. The discussion of BofA clarifies that the estimated parameters depend on the scale of the observables. Rather than report the parameters themselves, we show quantiles of three derived statistics. First, the absolute value of net notionals provides an idea of

Table A.3: Statistics for estimation of derivatives position for all public banks

	for trading			not for trading		
equal-weighted	p25	p50	p75	p25	p50	p75
$E[\lvert\phi_t\rvert]$	0.2	1.0	5.2	0.8	5.7	15.0
$var\left(R_t\phi_t\right)/var\left(\Delta\tilde{F}_t\right)$	5.6	30.5	79.1	6.0	39.1	81.7
$\sigma_u/E\left[\lvert\phi_t\rvert\right]$	2.6	55.9	263.4	2.8	63.6	284.1
asset-weighted	p25	p50	75	p25	p50	p75
$E[\lvert\phi_t\rvert]$	0.2	0.6	1.7	4.7	7.4	10.8
$var\left(R_t\phi_t\right)/var\left(\Delta\tilde{F}_t\right)$	13.9	24.9	37.0	10.6	60.2	83.1
$\sigma_u/E\left[\lvert\phi_t\rvert\right]$	0.0	4.2	19.1	13.6	26.4	51.5

Notes: Quantiles of equally weighted (top panel) and asset-weighted (bottom panel) cross sectional distributions of three summary statistics from estimation output for all public banks. $E[\phi_t]$ is the sample average of the absolute value of the estimated net short notionals as a share of notionals. Variance ratio is ratio of sample variances of gain times net short notionals relative to change in adjusted fair value from (D-14). σ_u is the estimated volatility of innovations to net short notionals relative the mean absolute net short notionals.

the typical size of the state variable ϕ_t. Much like for BofA, we find small numbers in for-trading positions and larger numbers in not-for-trading positions. The asset-weighted numbers in the bottom half of the table show that net notionals as a share of total notionals are smaller for large banks, which engage more in intermediation.

The second statistic is the ratio of the variance of gains $R_t\phi_t$ relative to fair-value changes $\Delta\tilde{F}_t$. The interquartile range (comparing p75 with p25) is wider in the equal-weighted sample. Intuitively, small banks more often exhibit one of two extremes: a spell of positions that are driven by trading behavior and hence have a ratio close to zero or a position that is fixed for a long time, so fair value moves only with prices and the ratio is one. Finally, we show the ratio of the standard deviation of the innovations u_t to the state ϕ_t relative to the mean absolute value of the state. We again observe a range, now with lower values in the asset-weighted sample, especially for the 75th percentile. This is because small banks more often exhibit short spells of derivatives activity. To capture fair-value dynamics, the code then has to allow for relatively larger changes in the state variables than is required for BofA, where the state changes slowly over time.

Overall, we take away two properties of the estimation results. First, the typical bank follows a relatively smooth path in net pay-floating notionals ϕ_t, with small innovations relative to existing positions. From equation (D-10), smooth net notionals translate into relative smooth exposure relative to notionals. Exposure relative to assets, our ultimate object of interest, is obtained by scaling with notionals and is, therefore, also smooth up to jumps in notionals themselves. This pattern is visible for BofA comparing notionals in the left panel of Figure A.12 and exposure in the bottom panel of Figure 3. Table A.3 shows that it is true more generally.

The second general property is that the contribution of gains $R_t\phi_t$ plays an important role in fair-value changes for the typical bank. This is what allows the code to infer the sign of the bank's exposure. We can see this for BofA by comparing the blue and orange lines in the top panel of Figure 3. The property is typical of large banks, as well as the majority of small banks. For many small banks, these ratios are even higher.

E Details on franchise value

In this appendix, we describe our definition of three components of bank value and provide summary statistics of their properties.

Components of bank value. We can think of a bank as a firm that produces intermediation services using capital and variable inputs, such as labor. Its tangible "capital stock" equals its net fixed income position FI_t plus a small stock of net non-fixed income assets NFI_t that include real estate and equity. Bank products include liquidity services from deposits and credit lines, the screening of borrowers, liquidity from market making, or asset management services. Their value is either earned as fees and commissions or is priced as spreads into interest rates on bank assets and liabilities. The cost of providing intermediation services consists of payments to labor and capital, including the return on the fixed income position, plus the cost of intermediate inputs.

By construction, the fixed-income position is the cumulative sum of portfolio incomes minus taxes and net sales of fixed-income assets. We define the non-fixed income asset position as the net book value of other bank assets and liabilities. We then define the *franchise value* FV_t of a bank as the difference between its market value and the sum of its two asset positions. Our measurement exercise thus delivers an estimate of FV_t as a residual from the identity

$$MV_t = FI_t + NFI_t + FV_t.$$

If all bank assets and liabilities were marked to market and the bank earned no rents, then the franchise value would be zero. The market value of equity would then also be equal to its book value, the cumulative sum of accounting income minus taxes, dividends, and net repurchases of equity. In practice, accounting rules allow income smoothing, so book equity moves less than asset positions, even if the franchise value is zero, such as for a competitive bank. Moreover, the

Table A.4: Comovements in components of bank value

	all public banks				small (>50)			
	MV	FI	NFI	FV	MV	FI	NFI	FV
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
mean	13.5	5.8	4.7	3.0	15.5	6.3	5.2	4.0
std dev.	3.0	1.4	0.7	2.9	3.4	2.0	0.5	3.5
corr MV		23.3	17.1	88.6		18.1	31.4	83.7
corr FI			-17.8	-18.9			-18.1	-36.9
corr NFI				2.9				26.3

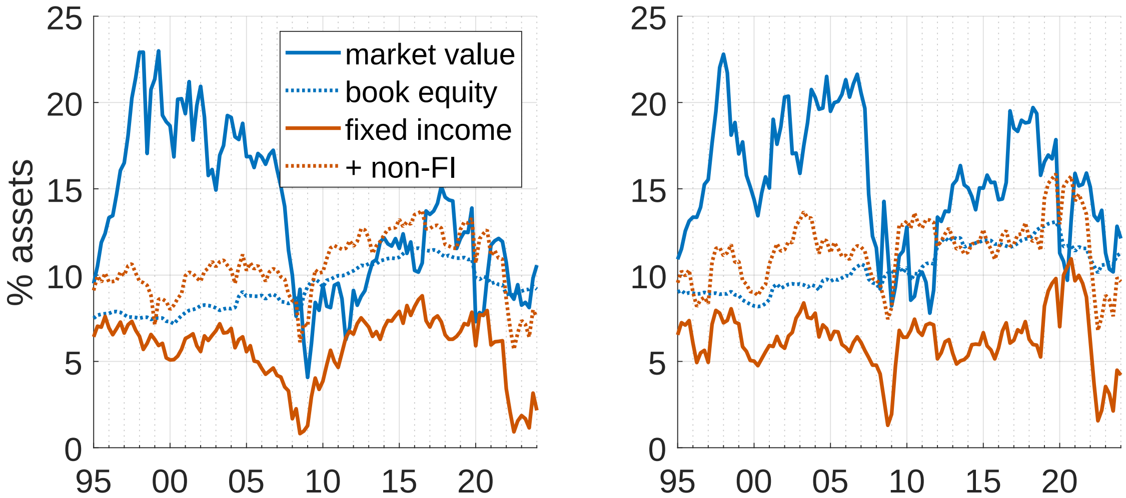
franchise value capitalizes future rents due to market power in product markets, segmentation, government guarantees, or adjustment costs to asset positions or equity. Such intangibles are valued by shareholders but not recorded on the balance sheet, even when positions are marked to market.

Figure A.14 shows the evolution of market equity, book equity, the fixed-income position, and the overall net portfolio position (including non-fixed-income assets) relative to total assets. The left panel shows data for all publicly traded banks, while the right panel isolates small banks. The franchise value appears as the difference between the market value and the overall net portfolio position. Table A.4 provides summary statistics for market value and each of its three components. We report mean levels and the standard deviations of year-on-year changes. To assess comovement, we also present the matrix of correlation coefficients for the changes.

Components of aggregate bank value over time. On average, over the entire sample, the three components of market value are of similar magnitude. However, there have been large shifts over time. Before the financial crisis, the franchise value was much larger, whereas it has been close to zero in recent years. It is by far the most volatile component of market value, with especially strong movements in the two recessions. Its decline mirrors the drop in banks' market-to-book ratio, which used to be above two and is now closer to one. Since 2012, market equity, book equity, and the overall portfolio position have been relatively close together and display a similar low-frequency hump with a peak shortly before the pandemic.

The contribution of the non-fixed-income position NFI_t has been fairly stable for the last 20 years. Indeed, the overall net portfolio position mimics all the large spikes in the fixed-income position FI_t. The non-fixed income position contains only a small component of volatile items that

Figure A.14: Components of bank value



Notes: Components of banks value in percent of total assets for all public banks (left panel) and small banks ranked below 50 (right panel). Market value is stock market capitalization. Solid orange lines show FI, dotted orange lines add NFI.

could contribute large additional movements: for all banks, equity holdings in the trading book are on average 90bp of assets, and the net fair value of non-fixed income derivatives relative to assets has a mean absolute value of 13bp. Positions in real estate and recorded intangibles instead move slowly. We conclude that the fixed-income position captures most volatility in bank portfolios. This is consistent with our result in Section 4 that fixed-income portfolio income accounts for most fluctuations in bank income. An interesting exception is the 2022 crisis, which we examine in more detail below.

Book equity is smooth relative to the fixed-income position since accounting rules allow the smoothing of income, including in times of stress. During those times, the net asset position declines more strongly than book equity since it records losses immediately. Moreover, shareholders recognize the present value of losses, so the market value of equity moves more closely with the net asset position than with book equity. In fact, market-to-book ratios dip below one after the financial crisis and the pandemic. The franchise value of the aggregate banking sector is mostly positive but also dips below zero after the two major recessions.

Changes in the fixed-income position comove positively with market value and are about half as volatile. The unconditional correlation between changes in the franchise value and the fixed-income position is negative. Intuitively, the franchise value reflects the yield curve level; its correlation with the five-year swap rate is about 80%. It thus not only declines with the fixed-income position in recessions but also declines when interest rates fall and banks expand using deposit funding, especially after 2012. This second force, discussed in Section 6, is sufficiently strong to drive the overall correlation. The franchise value also exhibits some unusual movements related to stock market booms, for example after the 2016 election.

The figures show a striking difference in the evolution of market values between small banks and the aggregate, and hence between small and large banks. Both groups started out with similarly large market values and franchise values relative to assets that dramatically declined in the financial crisis. After 2012, however, small banks managed to recover and arrived close to pre-crisis levels right before the pandemic. The big four banks, in contrast, which account for most assets in Figure 6, remained substantially below pre-crisis levels throughout. Another difference between large and small banks is that small banks hold essentially no equity and non-fixed-income derivatives positions. However, this feature does not matter for the dynamics of portfolio positions.

Bank value in 2022-3. Figure 13 in the text shows the cross-sectional relationship between the fixed-income position FI and the market value of equity MV for the recent banking crisis. The left panel shows both positions relative to assets at the end of 2021, right before interest rates spiked up. The right panel shows changes in both ratios between 2021:Q4 and 2023:Q1. The top panel of Table 4 reports asset-weighted averages by group of banks at the end of 2021 and changes over the 5 crisis quarters relative to 2021 assets. Here we further break out the level and change in the fixed-income position and the franchise value.

The left panel of Figure 13 shows a positive association between MV and FI relative to assets. Banks that deliver more value per dollar of assets hold larger fixed-income portfolios. For the average bank, the market value is twice as large as its fixed-income position. The multiple is larger for most top banks and smaller for small banks. Non-fixed-income assets make up another large chunk of bank value, about 5% of assets for each group. As of 2012, the franchise value was comparatively small, especially for the top banks.

Over the crisis period, the market value and the fixed-income position strongly declined together, much more so than what the historical experience in Table A.4 would have suggested. In the right panel of Figure 13, we add an asset-weighted regression line in blue with a slope of 0.55. At the bank-group level, fixed-income changes account for more than 80% of the market-value decline for banks outside the big 4. For the largest banks, there are offsetting effects from increases in franchise values and non-fixed-income assets. Still, the drop in the fixed-income position accounts for more than 60% of the market-value decline for big 4 banks.

To correctly assess the contribution of movements in fixed-income positions to those in market values, it is important to compare *changes* in the two values relative to assets and not, say, percentage changes. Since franchise values are large and heterogeneous, movements in fixed-income positions lead to different percentage changes in market values, holding franchise values constant. Comparing percentage changes would thus lead us to miss the fact that a large part of market-value changes in the recent crisis reflects changes in the fixed-income position.

F Decomposition

F.1 Dynamics of bank risk exposures

This appendix collects supplementary results on the dynamics of the aggregate banking sector. We first consider growth rates in risk exposure, that is, a version of Figure 7 in differences. We then decompose those changes into price changes and trading to assess the importance of asset illiquidity for the adjustment of exposures.

Timing of risk exposures. Since levels of exposure change slowly, Figure 6 makes it hard to see high-frequency fluctuations. The complementary Figure A.15 decomposes growth rates of exposure for interest rate risk (top panel) and credit risk (bottom panel) with the same color scheme. At any date, the shaded contribution of an individual position is the change in that position relative to total risk exposure in the previous quarter, which can be positive or negative. One takeaway is that debt and derivatives were tools to adjust the interest-rate exposure before the financial crisis but have been much less prominent since 2012.

A second key fact from the figure is that the two risk exposures move strongly together. This is true not only at business cycle frequencies—risk exposures increase just before recessions and sharply decline thereafter—but also at higher frequencies around financial events, such as the 2002 stock market crash or the 2011 European crisis. We finally note that fluctuations in risk positions are often due to *expansion at different rates*, not from actual reductions in risk. For example, the risk contribution due to loans rarely declines, except right after crises. Nevertheless, there are large fluctuations in the contribution of loans to assets. This is in contrast to securities and derivatives, where we observe more quarters with negative contributions.

Deposit growth and risk taking If market mistiming is connected to liquidity provision, deposit growth and growth of risk positions should move closely together. Figure A.16 decomposes the year-on-year percentage change in total assets of all public banks. The top panel shows asset-side components: we color the change in interest-rate and credit-risk exposures over initial assets, leaving cash as gray. The bottom panel shows liability-side components and colors the change in deposits over initial assets. For context, we add the five-year swap rate as a green solid line. Table A.5 summarizes correlations for the full sample and after 2012, and also breaks out the

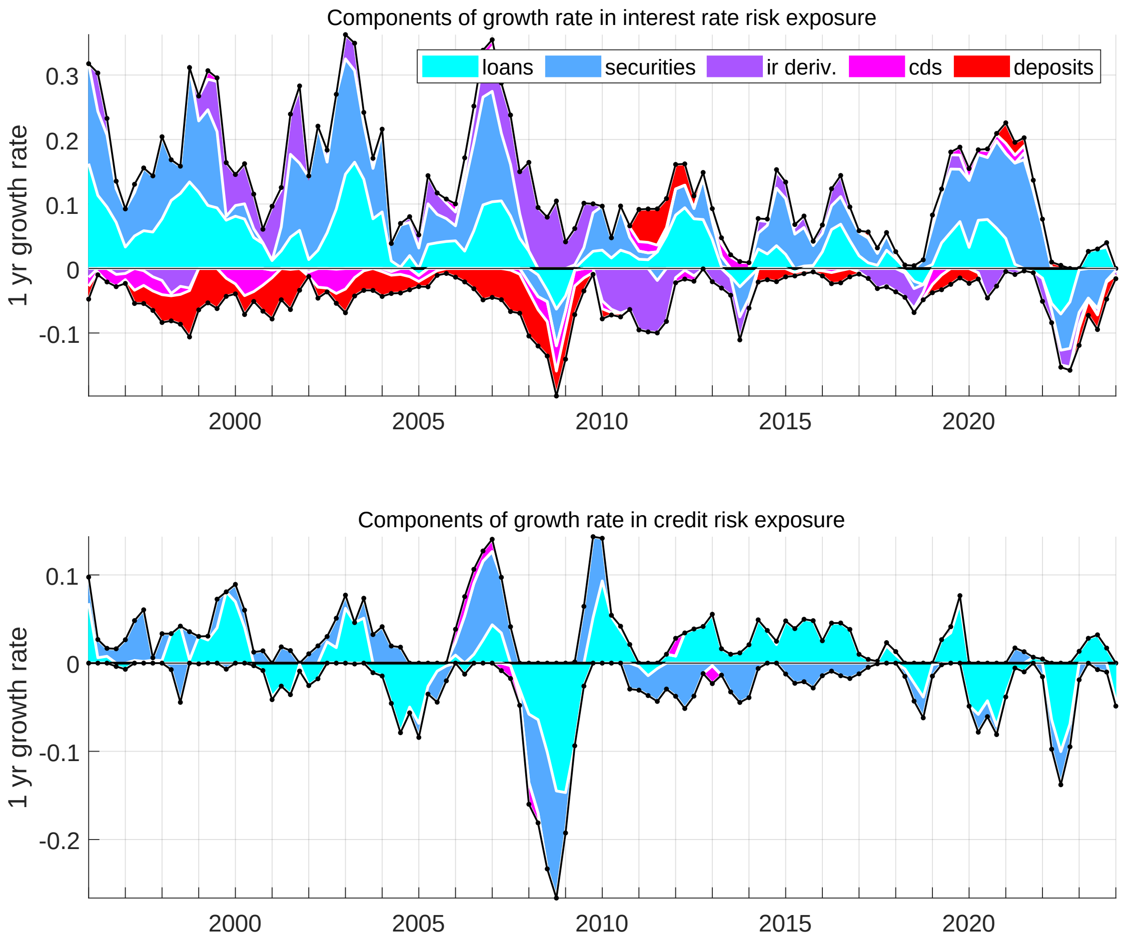


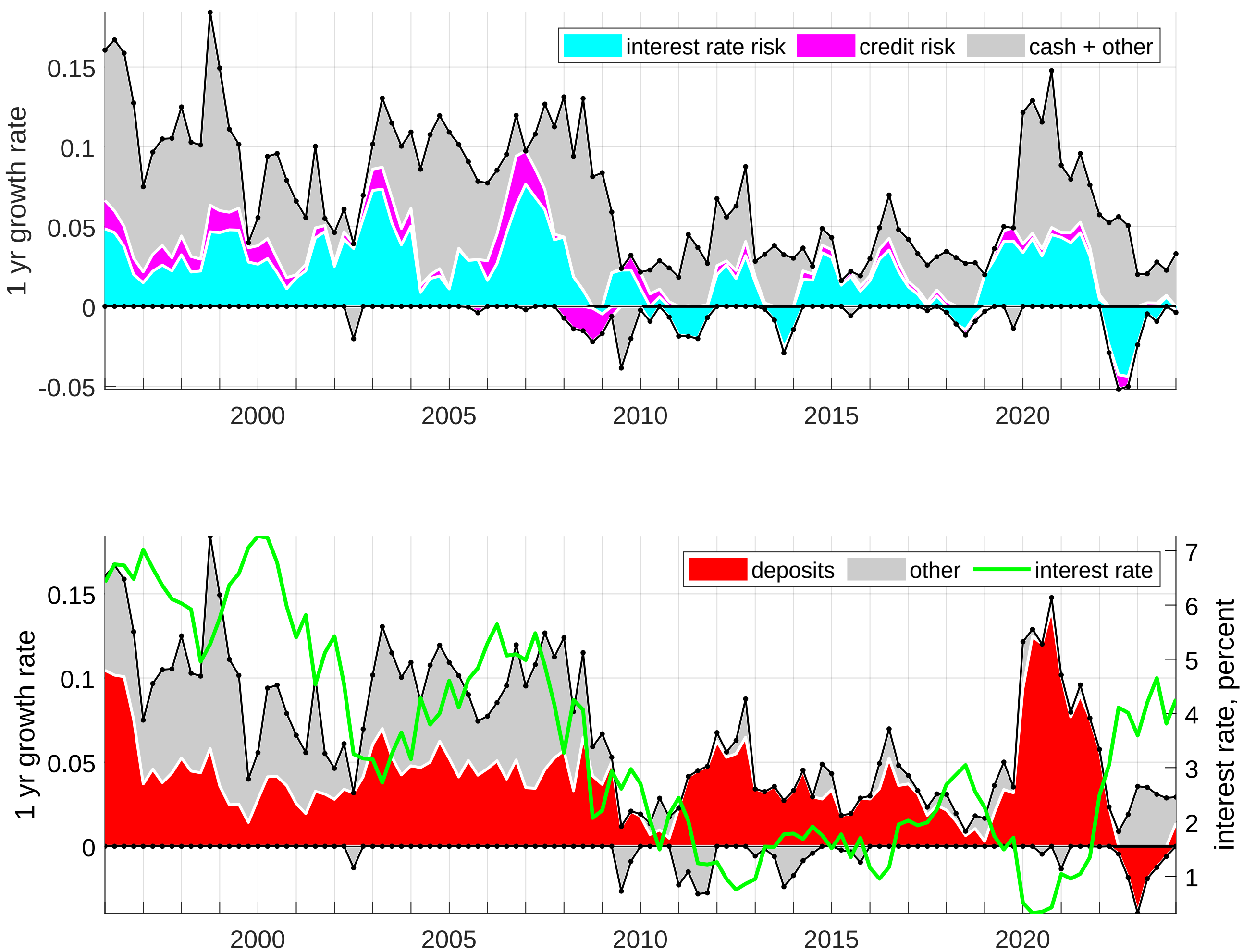
Figure A.15: Contributions of balance sheet positions to growth in risk exposure

small banks.

The figure illustrates the close connection between deposit inflows and growth in interest rate risk, especially since 2012. Every burst of deposit growth that follows a decline in interest rates is accompanied by a burst in interest-rate risk exposure. Since 2012, the correlation between changes in deposits and interest-rate risk is 75%. During this period, deposit growth also accounted for the overwhelming majority of bank-liability growth. Before the financial crisis, when banks relied more on other non-deposit funding (yellow in Figure 7), the comovement is somewhat weaker. Moreover, we saw atypical deposit outflows as the crisis was unfolding even as interest rates fell. Still, the correlation is 30% before 2012.

For small banks, who have always relied more on deposits, the comovement of risk exposure

Figure A.16: Contributions of risk and deposits to asset growth



Notes: Decompositions of year-on-year percentage change in assets for all public banks into change in interest-rate risk over initial assets, change in credit risk over initial assets and all other assets (top panel) and into change in deposits over initial assets and all other liabilities (bottom panel). Bottom panel adds 5-year swap rate as green line (right axis).

and deposit growth is large throughout the sample. Table A.5 shows correlations above 86% both for the full sample and since 2012. A key difference between large and small banks is the period of rising interest rates after 2004. During this time, small banks experienced low deposit growth and as a result did not build risk exposures, whereas large banks acquired risk using wholesale funding sources. Other funding severs the tight connection between risk and deposits that we always have for small banks and recently also for large banks. We thus again find our overall theme that large banks have come to resemble small banks in the period after 2012.

Table A.5 also reports correlations of deposit and interest-rate risk changes with changes in

Table A.5: Comovements in banks' risk exposures

	all public banks			small (>50)		
Begin	1995	1995	2012	1995	1995	2012
End	2024	2011	2024	2024	2011	2024
Correlations	(1)	(2)	(3)	(4)	(5)	(6)
int. rate risk, credit risk	61	55	87	92	94	88
int. rate risk, deposits	48	24	71	86	86	90
credit risk, deposits	23	24	50	87	86	78

Notes: Correlation coefficients in percent between asset-weighted average interest-rate and credit-risk exposures as well as deposits, all measured in percent of assets.

credit risk. The two risk exposures move strongly together. At the same time, *both* risk exposures comove strongly with deposits. Credit risk moves relatively more with deposits before 2012, when it was a larger share of portfolios. We take away that there is also a link between deposits and building credit risk. Such a link is consistent with NIM smoothing if, for example, banks earn spreads from loan opportunities that also require incurring some duration risk. More broadly, when banks have access to cheap deposit funding, they buy assets to back deposits and they select longer term assets they find profitable, which more recently had more interest rate risk, but had more credit risk before the financial crisis.

The figure also makes two other smaller points. First, the relationship between deposit flows and interest rates is nonlinear. There is more sensitivity to interest-rate changes recently when the level of rates is low, which goes along with stronger comovement between deposits and interest-rate risk. Second, the relationship between deposits and risk is not only stronger for small banks but also reflects relatively more stationary movements, alternating periods of both positive and negative growth. For large banks, we see this pattern only after the financial crisis. As we have seen in Figure 6, much of the dynamics for large and medium-sized banks before 2008 had to do with consolidation and overall growth: there is virtually no shrinkage in any position. This transition is now over, and large banks look more like small banks.