Banking on Deposits: Maturity Transformation without Interest Rate Risk

ITAMAR DRECHSLER, ALEXI SAVOV, and PHILIPP SCHNABL*

ABSTRACT

We show that maturity transformation does not expose banks to interest rate risk—it hedges it. The reason is the deposit franchise, which allows banks to pay deposit rates that are low and insensitive to market interest rates. Hedging the deposit franchise requires banks to earn income that is also insensitive, that is, to lend long term at fixed rates. As predicted by this theory, we show that banks closely match the interest rate sensitivities of their interest income and expense, and that this insulates their equity from interest rate shocks. Our results explain why banks supply long-term credit.

A DEFINING FUNCTION OF BANKS is maturity transformation—borrowing short term and lending long term. This function is important because it supplies firms with long-term credit and households with short-term liquid deposits. In textbook models, banks engage in maturity transformation to earn the average difference between long-term and short-term rates, that is, to earn the term premium. However, doing so exposes them to interest rate risk: an unexpected increase in the short rate increases banks' interest expense relative to their interest income, pushing down net interest margins and depleting banks' capital. Interest rate risk is therefore viewed as fundamental to the economic model of banking, and it underlies the discussion of how monetary policy impacts the banking sector.[1]

In this paper we show that despite having a large maturity mismatch banks do not take on significant interest rate risk. Rather, because of the deposit franchise,

*Itamar Drechsler is at the Wharton School, University of Pennsylvania. Alexi Savov and Philipp Schnabl are at New York University Stern School of Business. Drechsler and Savov are also with NBER, Schnabl is also with NBER and CEPR. We thank Markus Brunnermeier, Eduardo Dávila, John Driscoll, Mark Egan, Andreas Fuster, Mark Flannery, Raj Iyer, Arvind Krishnamurthy, Anna Kovner, Yueran Ma, Gregor Matvos, Monika Piazzesi, Anthony Saunders, David Scharfstein, Andrei Shleifer, Philip Strahan, Adi Sunderam, Bruce Tuckman, James Vickery, and seminar participants at the American Economic Association Meeting, BIS Research Meeting, Brandeis University, Carnegie Mellon, Chinese University in Hong Kong, ECB Monetary Policy Forum, FDIC, FRB Chicago, FRB New York, FRB Philadelphia, FRB San Francisco, Federal Reserve Board, Hong Kong University of Science and Technology, International Research Forum on Monetary Policy, LBS Summer Symposium, MIT Macroeconomics Seminar, NBER Summer Institute Corporate Finance, NBER Monetary Economics, Northwestern Macroeconomics Seminar, Ohio State University, Office of Financial Research, Princeton University, Purdue University, SITE, University of Amsterdam, University of Michigan, University of Pittsburgh, University of Rochester, and Yale University for their comments. We are also grateful for comments from two anonymous referees, the Associate Editor, and the Editor. We thank Patrick Farrell, Manasa Gopal, Pauline Liang, and Andrew Teodorescu for excellent research assistance.

Correspondence: Philipp Schnabl, New York University Stern School of Business; e-mail: pschnabl@stern.nyu.edu.

[1] In 2010, Federal Reserve Vice Chairman Donald Kohn argued that "Intermediaries need to be sure that as the economy recovers, they aren't also hit by the interest rate risk that often accompanies this sort of mismatch in asset and liability maturities" (Kohn (2010)). See also Boivin, Kiley, and Mishkin (2010).

maturity transformation actually reduces the amount of interest rate risk banks take on. Two essential properties of the deposit franchise drive this result. First, the deposit franchise gives banks market power over retail deposits, which allows them to borrow at rates that are both low and insensitive to market interest rates. Second, while running a deposit franchise incurs high operating costs (branches, salaries, marketing, technology), these costs do not vary much over time and hence are also insensitive to interest rates. Thus, even though deposits are short-term, funding via a deposit franchise resembles funding with long-term fixed-rate debt.

It is therefore natural for banks to hedge their deposit franchise by holding long-term fixed-rate assets. Indeed, since deposits are very large, so too are banks' long-term asset holdings. Thus, we argue that a big maturity mismatch actually insulates banks' profits from interest rate risk.

We show empirically that this is true in the aggregate: bank profits are insensitive to even very large fluctuations in interest rates. It is also true in the cross section: banks that have a stronger deposit franchise, and hence less sensitive interest expense, hold more long-term assets. Moreover, there is a close quantitative match: banks with less sensitive interest expense have one-for-one less sensitive interest income, which makes their profits fully hedged against interest rate shocks.

Our findings have several important implications. First, they provide a new answer to the fundamental question in banking of why deposit-taking and long-term lending occur within the same institution (e.g., Kashyap, Rajan, and Stein (2002)). This question underlies the renewed debate on the separation of deposit-taking and long-term lending (Friedman (1960), Cochrane (2014)). Our results suggest that deposit-taking and long-term lending have important synergies. In particular, deposit-taking is a natural hedge for the provision of long-term credit, which offers one reason they should *not* be separated. Second, our findings have implications for the transmission of monetary policy. In particular, they imply that banks are largely insulated from the balance sheet channel of monetary policy, under which interest rate shocks influence banks' lending by changing their net worth (Bernanke and Gertler (1989), Bernanke, Gertler, and Gilchrist (1999)).[2] More broadly, our results show that in a world in which interest rates fluctuate widely, the deposit franchise allows banks to provide long-term, fixed-rate loans without taking on interest rate risk.

We begin our analysis by documenting that banks engage in significant maturity transformation. Aggregate bank assets have an average estimated duration of 3.7 years, versus only 0.3 years for liabilities. This mismatch of about 3.4 years is large and stable over time. It implies that if banks paid market rates on their liabilities, a 100 bp level shock to interest rates would cause a cumulative 340 bp reduction in net interest margins (interest income minus interest expense, divided by assets) over the following years. This loss in profits would lead in turn to a 3.4% decline in the book value of assets relative to liabilities over the same period. This is a very large hit for banks, amounting to four years' worth of profits given that the industry's return on assets is less than 1%. Moreover, although it would take time for the losses to be

[2] Drechsler, Savov, and Schnabl (2017) present an alternative channel of monetary policy to bank lending that does not rely on variation in banks' net worth.

reflected in book values, investors would immediately price the full 3.4% decline in assets into banks' market values, and since banks are levered about ten to one, their net worth would drop by 34%.

We find that in practice a 100 bp shock to interest rates induces only a 4.2% drop in banks' net worth, a value that is an order of magnitude smaller than that implied by their duration mismatch. We obtain this result by regressing the return on a portfolio of bank stocks on the change in the one-year rate around Federal Open Market Committee (FOMC) meetings. In addition to being small, this sensitivity is very similar to that of the overall market portfolio (which drops by 3.7%) and is close to the median for the Fama-French 49 industries. Thus, banks are no more exposed to interest rate shocks than non-financial firms.[3]

To understand this result, we look at the interest rate sensitivity of banks' cash flows. We find that, consistent with their low equity sensitivity but in stark contrast to the textbook view, aggregate bank cash flows are insensitive to interest rate changes. Since 1955, net interest margins (NIM) have stayed in a narrow band between 2.2% and 3.8% even as the short rate has fluctuated widely and persistently between 0% and 16%. Furthermore, yearly NIM changes have had a standard deviation of just 0.15% and zero correlation with changes in the short rate. Thus, fluctuations in NIM have been both extremely small and unrelated to changes in interest rates.

We show that the insensitivity of NIM to the short rate is explained by banks' deposit franchise. To do so, we separate NIM into its two components, interest income and interest expense (both scaled by assets), and compare their interest rate sensitivities. We find that interest income has a low sensitivity to the short rate. This is expected because bank assets are primarily long-term and fixed-rate, hence the income they generate is locked in for term. The surprising finding is that the sensitivity of banks' interest expense is just as low, despite the fact that bank liabilities are overwhelmingly of zero or near-zero maturity. This apparent paradox is explained by the fact that having a deposit franchise gives banks substantial market power over retail deposits (Drechsler, Savov, and Schnabl (2017)). In particular, market power allows banks to keep their deposit rates low even when the short rate rises. Since retail (core) deposits comprise over 70% of banks' liabilities, this low sensitivity carries over to their overall interest expense. The deposit franchise thus allows banks to simultaneously have a large duration mismatch and a near-perfect match of the interest rate sensitivities of their income and expense.

Of course, a deposit franchise is not free; on the contrary, banks pay high operating costs to maintain it. Banks invest in a network of retail outlets, marketing their products, servicing their customers, and offering the latest financial technologies. These costs account for the large 2% to 3% difference between banks' NIM and their bottom-line return on assets (ROA). However, while these costs are high, they do not vary with interest rates and are quite stable. Indeed, they resemble the oper-

[3] We interpret the impact of interest rates on equity values as a common discount rate shock that affects all firms (Bernanke and Kuttner (2005)). The important result is that the shock has no additional impact on banks relative to non-financial firms despite their large duration mismatch and high leverage.

ating expenses of non-financial firms. As a result, the insensitivity of banks' NIM to interest rates flows through to their ROA.

We present a simple model that captures these findings. In the model, banks pay a constant per-period operating cost to run their deposit franchise. This gives them market power, which allows them to pay a deposit rate that is only a fraction of the market short-term rate, as in Drechsler, Savov, and Schnabl (2017). The model shows that the deposit franchise functions like an interest rate swap whereby the bank pays the fixed leg and receives the floating leg. The fixed leg is the operating cost the bank pays to obtain market power, while the floating leg is the interest spread it charges depositors by paying them a low deposit rate. The value of the deposit franchise can then be viewed as the net present value of this swap (the present value of the floating leg minus the fixed leg). As with any interest rate swap, this value is exposed to interest rate changes. In particular, an increase in interest rates causes the present value of the fixed leg to fall, and since the swap is short the fixed leg, the value of the deposit franchise rises.[4] Thus, the deposit franchise has positive exposure to interest rates; equivalently, it has negative interest rate duration.

Banks hedge their deposit franchise by taking the opposite exposure on their balance sheets. They do so by providing long-term, fixed-rate credit to firms and households and by investing in long-term, fixed-rate securities (positive duration). Under free entry into the deposit market, the average deposit spread that banks charge just covers their operating costs and their net deposit rents are zero (i.e., the deposit franchise swap is fairly priced). In this case, banks earn very thin margins at very high leverage, so it is crucial for them to be tightly hedged. This requires that they perfectly match the sensitivities of their income and expense to the short rate, so that their NIM and ROA are unexposed. Thus, the model explains why banks' aggregate interest income and expense have the same sensitivity to the short rate, and why aggregate NIM and ROA are so stable.

An important insight from the model is that a fundamental part of banks' interest rate exposure—the exposure of the deposit franchise—is not captured in book assets or book liabilities. This is because neither the deposit spread banks earn nor the operating cost they pay are capitalized. However, banks' interest rate exposure does figure prominently in their profit and loss statement. This is why we analyze the interest rate exposure of banks' income and expense.

The model predicts that the sensitivities of interest income and expense should match bank-by-bank. We test this prediction in the cross section using quarterly data on U.S. commercial banks from 1984 to 2017.[5] For each bank we estimate an interest expense sensitivity, which we refer to as its interest expense beta, by regressing the change in its interest expense (divided by assets) on contemporaneous and lagged changes in the Fed funds rate and then summing the coefficients. We compute each bank's interest income beta analogously. The average expense and income betas are

[4] We can also think of this result in terms of the forward value of the swap's cash flows. The forward value increases because the cash flows of the floating leg (the deposit spread) rise relative to the cash flows of the fixed leg (operating costs).

[5] We have posted the code for creating our sample and the sample itself on our websites.

0.345 and 0.351, respectively, with substantial variation in the range of 0.1 to 0.6.

We find that expense and income betas match up very strongly across banks. The correlation is 52% among all banks and 61% among the largest 5% of banks. Corresponding slopes from a regression of income betas on expense betas are 0.810 and 1.051, respectively.[6] These results hold across the size distribution of banks. Moreover, they are unchanged when we control for time fixed effects in the beta estimation, or when we test for matching in a panel regression setting. The strong one-to-one matching implies that banks' profitability is essentially unexposed to interest rate risk. Indeed, ROA betas (computed analogously to expense betas) are close to zero across the board, as predicted by our model.

Our estimates predict that a bank with an expense beta equal to one would have an income beta close to one. Although these betas are outside the range of variation in our sample, they have predictive power out of sample. In particular, they fit money market funds, which obtain funding at the Fed funds rate (expense beta of one) and only hold short-term assets (income beta of one). Hence, even though money market funds are not part of our sample, our results can explain their business model of investing in short-term assets and issuing shares that pay the short rate.

The insensitivity of banks' profits to interest rate shocks is confirmed by our analysis of bank stocks. Following the methodology we used for the bank industry portfolio, we estimate firm-level "FOMC betas" for all publicly traded commercial banks. As in the aggregate, the average FOMC beta of banks is small and close to that of nonfinancial firms. More importantly, there is a flat relationship between banks' FOMC betas and their expense and income betas. This finding shows that there is no relationship between a bank's asset duration, as reflected in its income beta, and the exposure of its net worth to interest rate risk. While this is puzzling from the vantage point of standard duration calculations and the balance sheet channel of monetary policy, it is a clear and direct implication of our model's prediction that banks are hedged against interest rate shocks.

We also directly test whether banks with low expense betas invest more in long-term fixed-rate assets. The answer is yes: there is a strong negative relationship between a bank's interest expense beta and the repricing maturity of its assets.[7] The slope of this relationship is -4.5 years, which is large and close to the average repricing maturity of bank assets. It again extrapolates to fit the duration of money market funds' assets.

We consider two main alternative explanations for our matching results. One possibility is that banks with higher expense betas face more liquidity (run) risk, which leads them to hold more short-term assets as a buffer. Although this explanation does

[6] We view the largest 5% of banks as the economically important sample given the extremely skewed distribution of bank size. The slightly smaller coefficient for all banks is concentrated among the smaller banks. These banks' income betas are slightly higher than their expense betas. Thus, to fully hedge they should have a slightly *larger* duration mismatch.

[7] An asset's repricing maturity is defined as the time until its interest rate resets. This is distinct from remaining maturity, which is the time until the asset terminates. An example that illustrates the difference is a floating-rate bond: its repricing maturity is one quarter while its remaining maturity can be many years. Repricing maturity thus captures whether an asset is both long-term and fixed-rate.

not predict the one-for-one sensitivity matching we see, it goes in the right direction. We address it by analyzing the shares of loans versus securities on bank balance sheets. Since loans are far less liquid than securities, the liquidity risk explanation predicts that high-expense-beta banks should hold more securities and fewer loans. We find the exact opposite: it is low-expense-beta banks that hold more securities and fewer loans. This result is consistent with our model because the average duration of securities (primarily agency mortgage-backed securities (MBS)) is much higher than that of loans. Thus, liquidity risk cannot explain our results.[8]

We also consider the possibility that the sensitivity matching we observe is the product of market segmentation. Perhaps banks with more market power over deposits also have more long-term lending opportunities. This explanation also does not predict one-for-one sensitivity matching. Nevertheless, we test it by checking whether banks match the income betas of their securities holdings to their expense betas. Since securities are bought and sold in open markets, they are not subject to market segmentation. We once again find matching, even when we focus narrowly on banks' holdings of Treasuries and agency MBS. This result shows that banks actively match their interest income and expense sensitivities.

In a final set of tests, we provide direct evidence for the market power mechanism underlying our model. We do so by exploiting two sources of geographic variation in deposit market power. The first is variation in local market concentration. We find that banks that raise deposits in more concentrated areas have lower expense betas and lower income betas, with a matching coefficient that is again close to one.

The second source of variation is variation in branch-level rates that banks pay on retail deposit products (interest checking, savings, and small time deposits) using data from the provider Ratewatch. These products are marketed directly to households in local markets and thus are the source of banks' market power. They are also well below the deposit insurance limit and hence immune to credit and run risk. We regress changes in the average rates of these retail deposits by county on Fed funds rate changes to obtain a county-level retail deposit beta. We then average these county betas for each bank, weighting by the county's share of the bank's branches, to obtain a bank-level retail deposit beta. We also estimate an alternative version that controls for bank-time fixed effects in the estimation of the county-level betas.[9] We find that variation in banks' market power, as captured by their retail deposit betas, is strongly related to their overall expense betas, and that banks match this variation one-for-one with their income betas.

The rest of this paper is organized as follows. Section I discusses the literature.

[8] In addition to loans and securities, about 26% of banks make use of interest rate derivatives (see Internet Appendix Table IA.IV). In principle, banks can use these derivatives to hedge the interest rate exposure of their assets, yet the literature argues that they actually use interest rate derivatives to increase such exposure (Begenau, Piazzesi, and Schneider (2015)). We show that our sensitivity matching results hold for both banks that do and banks that do not use interest rate derivatives. Hence, derivatives use does not drive our results.

[9] This estimation uses only differences in deposit rates across branches of the same bank. It thus removes time-varying bank characteristics (e.g., loan demand), giving us a clean measure of local market power.

Section II examines the aggregate time series. Section III presents the model. Section IV describes the data. Section V contains our main sensitivity matching results. Section VI examines the composition of bank assets. Section VII links our results to market power. Finally, Section VIII concludes.

I. Related Literature

Banks issue short-term deposits and make long-term loans. This dual function underlies modern banking theory (Diamond and Dybvig (1983), Diamond (1984), Gorton and Pennacchi (1990), Calomiris and Kahn (1991),Diamond and Rajan (2001), Kashyap, Rajan, and Stein (2002), Hanson et al. (2015)). Central to this literature is the liquidity risk that arises from issuing run-prone deposits. Brunnermeier, Gorton, and Krishnamurthy (2012) and Bai, Krishnamurthy, and Weymuller (2018) provide quantitative assessments of this liquidity risk. In this paper we instead focus on the interest rate risk that arises from maturity transformation. Liquidity risk and interest rate risk are distinct as assets can be exposed to one but not the other. For instance, a floating-rate bond has liquidity risk but no interest rate risk (its duration is zero), whereas a Treasury bond has interest rate risk but no liquidity risk (it can be resold easily). A broader distinction is that liquidity risk arises in financial crises whereas interest rate risk is of first-order importance at all times.[10]

Other explanations for why banks engage in maturity transformation rely on the presence of a term premium.[11] In Diamond and Dybvig (1983), an implicit term premium arises because households demand short-term claims but banks' productive projects are long-term. In a recent class of dynamic general equilibrium models, maturity transformation in the financial sector varies with the magnitude of the term premium and effective risk aversion (He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Brunnermeier and Sannikov (2016), Drechsler, Savov, and Schnabl (2018)). In Di Tella and Kurlat (2017), as in our paper, deposit rates are relatively insensitive to interest rate changes (due to a net worth constraint rather than market power). This makes banks less averse to interest rate risk than other agents and induces them to maintain a maturity mismatch in order to earn the term premium. The result is very large equity exposure: a 1% increase in interest rates causes banks' net worth to drop by 31%. This effect is about the same as the textbook duration calculation but an order of magnitude larger than what we find empirically.

In contrast to this literature, our paper offers a risk-management rather than a risk-taking explanation for banks' maturity mismatch. Under the risk-management explanation, maturity mismatch reduces banks' risk instead of increasing it. It also gives the strong quantitative prediction of one-for-one matching between the interest

[10] We focus on modern banking systems. Historical banking research suggests that in the 19th and early 20th century U.S. banks made fewer long-term loans and invested more in short-term securities (Bodenhorn (2003)).

[11] The term premium has declined and appears to have turned negative in recent years (see https://www.newyorkfed.org/research/data_indicators/term_premia.html). At the same time, banks' maturity mismatch has remained unchanged.

sensitivities of income and expense. We find this prediction to be borne out in the data.[12]

The empirical banking literature has looked at banks' sensitivity to interest rate shocks. In a sample of 15 banks, Flannery (1981) finds that bank profits have surprisingly low exposure and frame this as a puzzle. Flannery (1983) finds the same result using a sample of 60 small banks. English (2002) finds mixed results for exposure to level and slope interest rate shocks in a sample of 10 countries. Purnanandam (2007) argues that banks use interest rate derivatives to reduce the sensitivity of lending policy to interest rate shocks. Flannery and James (1984a) and English, Van den Heuvel, and Zakrajšek (2018) examine the cross section of banks' stock price exposures, but do not compare banks to other firms to see if they are special. The exposures in English, Van den Heuvel, and Zakrajšek (2018) are somewhat larger than ours because they include unscheduled emergency FOMC meetings. Nevertheless, they remain much smaller than predicted and only slightly larger than the exposure of non-financial firms.[13]

Other papers estimate banks' interest rate risk exposure from balance sheet data. Begenau, Piazzesi, and Schneider (2015) and Begenau and Stafford (2019) find that bank balance sheets are heavily exposed to interest rates. Rampini, Viswanathan, and Vuillemey (2020) find that banks hedge more of their interest rate risk if their net worth is larger. Our paper shows that banks' balance sheet exposure is hedged by the deposit franchise.

This result relates to the debate about whether bank balance sheets should be marked to market (e.g., Allen and Carletti (2008), Heaton, Lucas, and McDonald (2010)). Our analysis implies that for mark-to-market accounting to properly capture banks' interest rate risk, the deposit franchise would have to be capitalized on the balance sheet. Otherwise, as long as income from the deposit franchise is booked only as it accrues over time, it is consistent to do the same on the asset side.

Our paper connects with Drechsler, Savov, and Schnabl (2017) to create the following picture of the impact of interest rates on banks. Banks invest heavily in building a deposit franchise, which gives them market power. They exploit this market power by charging higher deposit spreads when interest rates rise. This makes deposits resemble long-term debt and leads banks to hold long-term assets so that their NIM and net worth are hedged. However, as Drechsler, Savov, and Schnabl (2017) show, to charge these higher spreads banks have to cut their deposit supply (like any monopolist) and therefore must contract their balance sheets. Thus, monetary policy exerts

[12] Consistent with the risk-management explanation, Bank of America's (2016) annual report states that "Our overall goal is to manage interest rate risk so that movements in interest rates do not significantly adversely affect earnings and capital." Section I of the Internet Appendix provides further discussion of bank risk management taken directly from the annual reports of the largest U.S. banks. The Internet Appendix is available at Philipp Schnabl's website. Our explanation is also consistent with case studies of bank interest rate risk management (e.g., Backus, Klapper, and Telmer (1994), Esty, Tufano, and Headley (1994)). For formal models of bank risk management, see Froot, Scharfstein, and Stein (1994), Freixas and Rochet (2008), and Nagel and Purnanandam (2020).

[13] Bernanke and Kuttner (2005) argue that the exposure of non-financial firms is due to an increase in the equity risk premium. Nakamura and Steinsson (2018) argue that the exposure comes from improved growth expectations.

a powerful impact on banks' credit supply, even as NIM and net worth are hedged.

Under this framework banks with more market power have both a larger maturity mismatch and a more sensitive credit supply. This can explain the finding of Gomez et al. (2021) that banks with a bigger income gap (a measure of maturity mismatch) contract lending more when interest rate rise. Moreover, our results suggest that banks should become less willing to hold long-term assets as their deposits flow out. This can shed light on the finding of Haddad and Sraer (2019) that the income gap negatively predicts bond returns.

A canonical example of interest rate risk in the financial sector comes from the Savings and Loan (S&L) crisis of the 1980s. S&Ls were mandated to hold only mortgages and hence had an exceptionally large duration mismatch (White (1991)). This was sustainable during the 1970s when deposit rate ceilings under Regulation Q reduced the interest sensitivity of deposits to essentially zero. It became unsustainable in the 1980s, however, when Regulation Q was repealed, causing deposit rates to jump. Thus, while S&Ls were hedged under the old regime, they became unhedged under the new one. This explains why they became insolvent.[14]

The deposits literature has documented the low sensitivity of deposit rates to market rates, a key ingredient in our paper (Hannan and Berger (1991), Neumark and Sharpe (1992), Driscoll and Judson (2013), Yankov (2014), Drechsler, Savov, and Schnabl (2017)). A subset of this literature (Flannery and James (1984b), Hutchison and Pennacchi (1996), Janosi, Jarrow, and Zullo (1999), O'Brien (2000)) estimates the effective duration of deposits, finding it to be higher than their contractual maturity, consistent with a low interest rate sensitivity.[15] Nagel (2016) and Duffie and Krishnamurthy (2016) extend the low sensitivity finding to a wider set of bank instruments.

A growing literature examines the effect of prolonged periods of low interest rates on bank profitability and lending (Brunnermeier and Koby (2018), Eggertsson et al. (2019)). Our analysis suggests that such periods could hurt bank profitability if they last longer than the maturity of banks' long-term assets. Wang (2018) finds that banks mitigate this effect by widening the spreads they charge on their loans.

The literature has also examined the relationship between deposit funding and bank assets. Kashyap, Rajan, and Stein (2002) emphasize the synergies between the liquidity needs of depositors and bank borrowers. Gatev and Strahan (2006) show that banks experience inflows of deposits in times of stress, which allows them to provide more liquidity to their borrowers. Hanson et al. (2015) argue that banks are better at holding fixed-rate assets than shadow banks because deposits are more stable than wholesale funding. Kirti (2020) finds that banks with more floating-rate liabilities extend more floating-rate loans. Egan, Hortaçsu, and Matvos (2017) examine the effect of deposit competition on financial fragility. Berlin and Mester

[14]Drechsler, Savov, and Schnabl (2020) provide further discussion of the impact of Regulation Q on deposit rates for banks and S&Ls.

[15]Consistent with low interest rate sensitivity, Adams et al. (2021) conduct a large-scale field experiment in the U.K. and find that most households do not move savings accounts to other banks even if they are informed about significantly higher deposit rates elsewhere.

(1999) show that deposits allow banks to smooth out aggregate credit risk. Our paper focuses on banks' exposure to interest rate risk and provides an explanation for the co-existence of deposit-taking and maturity transformation.

II. Aggregate Bank Interest Rate Risk

In this section we analyze the aggregate exposure of banks to changes in interest rates. We first document the extent to which banks engage in maturity transformation by estimating the durations of their assets and liabilities. We do so in two ways. First, we use data on repricing maturity from the U.S. Call Reports. Repricing maturity is a useful proxy for duration because it distinguishes between long-term fixed-rate assets and short-term floating-rate assets. Details on how it is calculated are provided in Section IV of the Internet Appendix.

Figure 1 plots the time series of the repricing maturity of bank assets and liabilities for the period 1997 to 2017. The average asset repricing maturity is 4.23 years and has been rising slightly. The average liabilities repricing maturity is 0.34 years and has been declining slightly. Thus, based on this measure, the aggregate banking sector exhibits a duration mismatch of about 3.9 years.

[Figure 1 about here]

A potential concern with the use of repricing maturity as a proxy for duration is that it ignores the effects of prepayment and amortization, which are common in the case of mortgages. To address this concern, in a second approach we estimate the duration of bank assets using the information about duration contained in banks' interest income. Consider a bank with only short-term assets (e.g., a money market fund). The bank's interest income moves one-for-one with the short-term interest rate. At the other extreme, the interest income of a bank that buys and holds only long-term (fixed-rate) assets moves one-for-one with a moving average of current and past long-term interest rates. In between these two extremes, a bank with some long-term and some short-term assets has interest income that is a combination of these two interest income "factors." We can estimate it using a simple regression of banks' interest income on the factors. The resulting coefficients can be interpreted as the weights of a bond portfolio that mimics the asset side of bank balance sheets. The duration of that portfolio gives us a proxy for the duration of bank assets. Details on this procedure are provided in Section IV of the Internet Appendix.

Using this approach, we find that the average duration of bank assets is 3.7 years. As expected, this number is slightly below that using repricing maturity but the two are quite similar. The implied duration mismatch between bank assets and liabilities is 3.4 years.

A duration mismatch of 3.4 years is economically large. It implies that a 1% level shock to interest rates would cause the value of bank assets to decline by 3.4% relative to liabilities. Banks' ten-to-one leverage amplifies this number to a 34% decline in equity values. Thus, one way to test if maturity transformation exposes banks to interest rate risk is by estimating the sensitivity of their equity prices to interest rate shocks. We do so by regressing the returns of an industry portfolio of bank stocks on changes in the one-year Treasury rate around FOMC meetings. For comparison, we also estimate this sensitivity for other industries and for the market portfolio.[16]

Figure 2 displays the results. The coefficient for banks is -4.24, which implies that bank stocks drop by 4.24% for every 1% positive shock to the one-year rate. This number is an order of magnitude smaller than that predicted by the duration mismatch. Moreover, banks' sensitivity is very similar to that of the overall market portfolio (-3.71), and ranks only 20^{th} among the 49 industries. Thus, in spite of their large duration mismatch, banks are no more exposed to interest rate shocks than the typical non-financial firm.

[Figure 2 about here]

This result implies that banks have an asset whose interest rate exposure offsets their duration mismatch yet does not appear on the balance sheet. We can detect it by looking closely at banks' cash flows, where it must offset the influence of the duration mismatch. The duration mismatch implies that an increase in interest rates should cause banks' interest expense to rise relative to their interest income, and hence their difference, the net interest margin (NIM), should fall.

We find that this is not what happens. Panel A of Figure 3 plots banks' aggregate NIM from 1955 to 2017.[17] It also plots the short-term rate (the Fed funds rate), which has varied widely and persistently over the decades, from 2% in the 1950s to over 16% in the early 1980s then back to 0% after the 2008 financial crisis. On top of these decades-long fluctuations, the short rate has gone through the peaks and troughs of numerous business cycles, each measuring between three and five percentage points. This shows there has been a lot of interest rate risk.

[Figure 3 about here]

Despite this, aggregate bank NIM has never strayed outside a narrow band between 2.2% and 3.8%. Moreover, movements within this band have been gradual and have no obvious connection to interest rates. Formally, NIM changes have an annual standard deviation of just 0.15% and zero correlation with the Fed funds rate. To complete the picture, the figure also plots banks' ROA (net income divided by assets), which is a standard measure of profitability. The figure shows that ROA is just as insensitive to interest rates as NIM. Overall, the lack of exposure of banks' cash flows to interest rates is consistent with the low exposure of their equity.

The asset that reconciles banks' low-cash-flow exposure with their high-balance-sheet exposure is the deposit franchise. We can hone in on its impact by separating

[16] We report the regression results in Section I of the Internet Appendix. We use the 49 Fama-French industry portfolios, available from Ken French's website. We use a one-day window around FOMC meetings. The sample starts in January 1994 (when the FOMC began making announcements) and ends in June 2007 (before the onset of the 2007 to 2009 financial crisis). We focus on the 108 scheduled meetings over this period (the five unscheduled ones are contaminated by other types of interventions). The results are unaffected if we use other maturities or if we control for slope changes.

[17] The data come from the Historical Statistics on Banking from the Federal Deposit Insurance Corporation (FDIC). The sample starts in 1955, the year the Fed funds rate becomes available.

the two components of NIM: interest income and interest expense (divided by assets). These are shown in Panel B of Figure 3. Interest income is close to a moving average of past interest rates, consistent with the high duration of bank assets. The rates on these assets are set at origination and remain locked in until they roll off, which makes interest income slow-moving and relatively insensitive to the short rate.

The surprising feature in Panel B of Figure 3 is that interest expense is as insensitive to the short rate as interest income. This is where the deposit franchise enters. Deposits make up over 70% of bank liabilities, and it is their zero or near-zero maturities that are responsible for the low overall duration of these liabilities. Yet, as the figure indicates, the rates that banks pay on deposits are much lower and smoother than the market short-term rate. As Drechsler, Savov, and Schnabl (2017) show, this is due to market power in retail deposit markets. Market power allows banks to keep deposit rates low even when market interest rates rise. As a result, banks can have both a large duration mismatch and insensitive cash flows at the same time, that is, they can engage in maturity transformation without interest rate risk.

To further highlight the importance of the deposit franchise, we contrast banks' cash flows with those of the Treasury mimicking portfolio.[18] Recall that the asset side of the Treasury mimicking portfolio is constructed to match banks' asset duration by providing the best possible fit to their interest income. We find that this occurs by investing 26.7% of the assets in the portfolio at the Fed funds rate and the remaining 73.3% in a buy-and-hold portfolio of 10-year Treasury bonds. On the liabilities side, the Treasury portfolio is funded by borrowing 66% at the Fed funds rate and 34% at the one-year Treasury rate. This matches the average repricing maturity of bank liabilities of 0.34 years.[19]

Panel A of Figure 4 plots the NIM of the Treasury portfolio, calculated in the same way as banks' NIM.[20] The Treasury portfolio NIM behaves exactly as predicted by its duration mismatch: it falls sharply whenever the short rate rises and jumps up when the short rate falls. Persistent shocks are especially powerful, with interest rates rising steadily from the beginning of the sample until the 1980s, causing the Treasury portfolio's NIM to be negative almost the whole time. Thereafter, as rates began their secular decline, it turned positive. Thus, the Treasury portfolio loses money in the entire first half of the sample, highlighting the extreme risk of having a large duration mismatch without a deposit franchise.

[Figure 4 about here]

Panel B of Figure 4 highlights this point further. Whereas banks' interest expense

[18] We thank Adi Sunderam for the suggestion.

[19] The details are in Section IV of the Internet Appendix . We use repricing maturity on the liabilities side because there it is not affected by prepayment or amortization and because the presence of market power makes Treasury rates a poor fit for deposit rates.

[20] Specifically, an asset's interest income is booked at its yield to maturity as of the purchase date. Book accounting therefore ignores fluctuations in present values and books income only as cash flows are realized. An alternative approach is to book valuation changes as income when they occur, rather than waiting for the cash flows to arrive. The problem with this approach is that it requires estimating the large but unobservable present value of the deposit franchise and its fluctuations.

is low and smooth with respect to the Fed funds rate, the interest expense of the Treasury portfolio closely tracks the Fed funds rate. This is why the NIM crashes whenever the Fed funds rate rises. Thus, Figure 4 makes clear why the deposit franchise allows banks to engage in maturity transformation without exposing their bottom lines to interest rate risk.[21]

III. A Model of Bank Interest Rate Risk

We provide a simple model of a bank's investment problem to explain our aggregate findings and obtain cross-sectional predictions. Time is discrete and the horizon is infinite. The bank funds itself by issuing risk-free deposits. The bank's problem is to invest in assets that maximize the present value of its future profits, subject to the requirement that it remain solvent so that its deposits are indeed risk free. For simplicity we assume that the bank does not issue any equity. While it is straightforward to incorporate equity, the bank is able to avoid losses and thus does not need to issue equity.

To raise deposits, the bank operates a deposit franchise at a cost of c per deposit dollar. This cost is due to the investment the bank has to make in branches, salaries, advertising, and so on to attract and service its depositors. Importantly, the deposit franchise gives the bank market power, which allows it to pay a deposit rate of only

$$r_t^d = \beta^{Exp} f_t, \tag{1}$$

where $0 < \beta^{Exp} < 1$ and f_t is the economy's short-rate process (i.e., the Fed funds rate).[22]

Drechsler, Savov, and Schnabl (2017) provide a model that micro-founds the deposit rate in (1) as an industry equilibrium among banks with deposit market power. The strength of a bank's market power is captured by the spread it is able to charge its depositors, $(1-\beta^{Exp})f_t$. A bank with high market power has a low β^{Exp} and charges a high spread, while a bank with low market power, such as one funded mostly by wholesale deposits, has a β^{Exp} close to one and charges almost no spread.

On the asset side, we assume that markets are complete and prices are determined according to the stochastic discount factor m_t. Like all investors, banks use this

[21] Begenau and Stafford (2019) argue that the low interest exposure of banks' NIM may be an artifact of book accounting. Figure 4 shows that this is not the case. The NIM of the Treasury portfolio is also calculated according to book accounting rules, yet it has an extremely large interest rate exposure. Moreover, leaving accounting aside, the low sensitivity of bank equity values to interest rate shocks (−4.24% versus the −34% implied by their duration mismatch) is inconsistent with substantial interest rate risk exposure.

[22] Note that deposits here are short-term, as reflected in their dependence on the short rate. While adding long-term debt to the model is straightforward, it would not change the mechanism and hence we leave it out. In any case, as Figure 1 shows, banks' liabilities are largely short-term.

stochastic discount factor when valuing profits.[23] Their problem is thus

$$V_0 = \max_{INC_t} E_0\left[\sum_{t=0}^{\infty}\frac{m_t}{m_0}\left(INC_t - \beta^{Exp} f_t - c\right)\right] \tag{2}$$

$$\text{s.t. } E_0\left[\sum_{t=0}^{\infty}\frac{m_t}{m_0} INC_t\right] = 1 \tag{3}$$

$$\text{and } INC_t \geq \beta^{Exp} f_t + c, \tag{4}$$

where INC_t is the time- and state-contingent income or payout stream generated by the bank's asset portfolio. The bank's problem is normalized to one dollar of deposits, which is without loss of generality since it scales linearly in deposit dollars. Equation (3) gives the budget constraint: the present value of future income must equal its current value of one dollar. Equation (4) is the solvency constraint: the bank must generate enough income each period to pay its interest expense, $\beta^{Exp} f_t$, and operating costs, c.

The bank's solvency risk is two-sided. On the one side, its interest expense rises with the short rate ($\beta^{Exp} > 0$), so it must ensure that its income stream is sufficiently positively exposed to f_t, as otherwise it will become insolvent when f_t is high. This means that a sufficient fraction of the bank's portfolio must resemble short-term bonds, whose interest payments rise with the short rate. This condition echoes the standard concern that banks should not be overly maturity-mismatched, that is, that a large-enough fraction of their assets should be short-term. Yet there is an important difference. The standard concern is based on the short maturity of deposits, which suggests a high sensitivity to the short rate. However, due to market power, the bank's deposit sensitivity β^{Exp} can be well below one, in which case its portfolio share of short-term assets can be below one as well.

The other side of the bank's solvency risk is due to its operating costs c, which are insensitive to the short rate. To cover these costs, the bank's income must be *insensitive* enough to f_t, as otherwise the bank will become insolvent when f_t is low. Thus, the bank must hold sufficient long-term fixed-rate assets, which produce an income stream that is insensitive to the short rate. Put differently, when f_t is low, the bank's deposit franchise generates only a small deposit spread yet continues to incur the same level of operating costs. To hedge against this low-rate scenario, the bank must hold sufficient long-term assets.

We can highlight the contribution of the deposit franchise by decomposing the value of the bank's future profits into a balance sheet component and a deposit franchise component:

$$V_0 = E_0\left[\sum_{t=0}^{\infty}\frac{m_t}{m_0}\left(INC_t^{\star} - f_t\right)\right] + E_0\left[\sum_{t=0}^{\infty}\frac{m_t}{m_0}\left[\left(1-\beta^{Exp}\right)f_t - c\right]\right]. \tag{5}$$

The first term captures the balance sheet component: the assets generate income of

[23] This is a basic distinction between our framework and the literature, which typically models banks as separate agents with distinct risk preferences or beliefs.

$INC_t^\star$ and the liabilities, which are short-term, incur expenses of f_t. The second term is the deposit franchise. It generates income given by the deposit spread $\left(1-\beta^{Exp}\right)f_t$ and incurs expenses given by the fixed operating costs c. The deposit franchise can be viewed as an interest rate swap in which the bank pays the fixed rate c and receives the floating rate $\left(1-\beta^{Exp}\right)f_t$.[24] Thus, the deposit franchise has a negative duration. As for any pay-fixed swap, the value of the deposit franchise increases with interest rates. [25]

The bank can hedge this exposure by taking the opposite exposure through its balance sheet. A complete hedge is necessary when excess deposit rents are zero, as is the case under free ex-ante entry into the banking industry.[26] In this case, the bank can generate just enough income to cover its expense each period. We obtain the following result.

PROPOSITION 1: *Under ex-ante free entry,* $V_0 = 0$ *and the bank's income stream is given by*

$$INC_t^\star = \beta^{Exp} f_t + c. \tag{6}$$

Hence, the bank matches the interest sensitivities of its income and expense:

$$\textit{Income beta} \ \equiv \ \beta^{Inc} \ = \ \frac{\partial INC_t^\star}{\partial f_t} \ = \ \beta^{Exp} \ \equiv \ \textit{Expense beta}. \tag{7}$$

This matching makes the bank fully hedged to any shock to current or expected future interest rates:

$$\frac{\partial}{\partial E_t[f_{t+s}]} V_t \ = \ 0 \quad \textit{for every } t, s \geq 0. \tag{8}$$

When there are no excess rents, the present value of future deposit spreads is equal to the present value of the operating costs. The bank must therefore apply its whole income stream to satisfying the solvency constraint, leading to the simple prediction that the bank matches the interest sensitivities of its income and expense. We test this prediction in the following sections by analyzing the cross section of banks.

It is worth pointing out that the bank can implement this strategy in various ways because asset markets are complete. The simplest way to do so is by holding standard bonds. In particular, the bank can invest a share β^{Exp} of its assets in short-term bonds, and the remainder $(1-\beta^{Exp})$ in long-term fixed-rate bonds. Alternatively, it could use derivatives or a more sophisticated trading strategy as long as it satisfies

[24] Jarrow and van Deventer (1998) also point out the analogy to interest rate swaps when valuing deposit liabilities and credit card balances under imperfect competition.

[25] Formally, the value of the deposit franchise simplifies to $\left(1-\beta^{Exp}\right) - cP_0^{consol}$, where $P_0^{consol} = E_0\left[\sum_{t=0}^{\infty} \frac{m_t}{m_0}\right]$ is the price of a consol bond with one dollar face value. Higher interest rates (lower discount factors m_t/m_0 for $t>0$) cause P_0^{consol} to fall, and hence the value of the deposit franchise rises.

[26] If we add bank equity to the model and it is small compared to assets, as in practice, banks will still hedge most of their interest rate risk.

equation (6).[27] Given that, the bank is fully hedged with respect to any and all shocks to the short rate or to expectations of its future path, including any changes in the term premium. This is because it is hedged period by period and state by state.

Finally, the model could be extended to allow bank assets to have default risk. This would lead to imperfect hedging since deposits do not hedge default risk. This extension would allow for an analysis of bank default risk, bank bailouts, and bank risk management. To keep the focus in this paper on maturity transformation and interest rate risk, we abstract from these important features of banks.[28]

IV. Data Sources

Bank data. Our bank data are from the U.S. Call Reports provided by Wharton Research Data Services. We use data from January 1984 to December 2017. The data contain quarterly observations of the income statements and balance sheets of all U.S. commercial banks. The data contain bank-level identifiers that can be used to link to other data sets.

Branch-level deposits. Our data on deposits at the branch level are from the FDIC. The data cover the universe of U.S. bank branches at an annual frequency from June 1994 to June 2017. The data contain information on branch characteristics such as the parent bank, address, and location. We match the data to the bank-level Call Reports using the FDIC certificate number as the identifier.

Retail deposit rates. Our data on retail deposit rates are from Ratewatch, which collects weekly branch-level deposit rates by product from January 1997 to December 2017. The data cover 54% of all U.S. branches as of 2013. Ratewatch reports whether a branch actively sets its deposit rates or whether its rates are set by a parent branch. We limit the analysis to active branches to avoid duplicating observations. We merge the Ratewatch data with the FDIC data using the FDIC branch identifier.

Fed funds data. We obtain the monthly time series of the effective Federal funds rate from the H.15 release of the Federal Reserve Board. We convert the series to the quarterly frequency by taking the last month in each quarter.

[27] In practice, it is likely that banks will implement this strategy using standard bonds. The reason is that more complicated strategies likely generate implementation costs, possibly due to increased monitoring need. Any nonzero implementation cost would break the equivalence in favor of the simplest strategy. Indeed, the aggregate evidence is consistent with implementation through standard assets. The simple strategy predicts a constant NIM and ROA, as shown in Figure 3, because banks match both interest income and interest expense. In contrast, strategies that rely on derivatives or the sale of assets also generate a constant ROA but do not necessarily lead to a constant NIM because capital gains do not enter NIM.

[28] Bank bailouts would not affect the results as long as they are efficient, that is, there would be no rents to bank equity holders (Philippon and Schnabl (2013)).

V. Bank Interest Rate Risk Hedging

A. *Methodology*

There are two approaches to analyzing whether banks hedge their interest rate risk. The present-value approach estimates the impact of interest rates on the market value of bank equity, while the cash flow approach estimates the impact of interest rates on banks' income and expense. The two approaches give consistent answers because the value of bank equity is the present value of future income minus the present value of future expense.

The two approaches are best illustrated with an example. Consider the case of a bank portfolio that consists of a fixed-rate four-year maturity bond with face value \$1 paying a coupon of $C\%$, and a liability that is a floating-rate four-year maturity bond with face value \$1 paying a coupon that equals the short rate r_t in year t. This yields a duration mismatch of about four years. Assume that the fixed-rate bond has a price of \$1 at the outset and, by construction, the floating-rate bond is always worth \$1. For simplicity, assume that forward rates are equal at all maturities at the outset and that an interest rate shock increases them in parallel at all maturities.

What is the impact of an increase in the interest rate by Δr under the present-value approach? The floating-rate liability's price remains fixed at \$1, as always. The fixed-rate bond's price drops immediately on impact. The decrease in its price is equal to the present value of a four-year annuity paying $\$\Delta r$, the amount that would be needed to keep the bond valued at par. This is approximately $\$4\Delta r$. Thus, the present-value approach would show that the bank's equity value drops by approximately $\$4\Delta r$, which makes sense since its duration mismatch is four.

How about the cash flow approach? The cash flow approach follows the future income and expense of the bank's assets and liabilities. By definition, the fixed-rate bond's cash flows do not change, so there is no increase in interest income. In contrast, the interest expenses owed on the floating-rate liability increase by $\$\Delta r$ for each of the four years, that is, the increase in future interest expenses is given by a four-year annuity paying $\$\Delta r$. Combining the asset and liability cash flows, the decrease in the bank's net future cash flows is given by a four-year annuity paying $\$\Delta r$, which is exactly the same conclusion we found using the present-value approach.

We emphasize that the cash flow approach does *not* add banks' unrealized capital gains or losses when analyzing future income and expense. The capital loss, which is the present value of a four-year $\$\Delta r$ annuity, is exactly equal to the decline in future net income. Adding the capital loss on top of the change in future income would result in double-counting. In contrast, under the present-value approach the effect on bank equity is equal to the capital loss. Put differently, the only difference between the two approaches is that the cash flow approach measures the impact on income over four years, while the present-value approach measures the entire impact immediately.

In our cross-sectional analysis, we start by using the cash flow approach. The reason is that we want to analyze income and expense separately and we observe both variables in bank call reports. We cannot do the same with the present-value approach because we do not separately observe the present value of banks' future income and expense, but only the net amount.[29] Having analyzed income and expense separately, we then analyze the net effect on bank income and expense. For this analysis we use both the cash flow approach and present-value approach since we observe the relevant variables for both, namely, NIM and ROA for the cash flow approach and the market value of bank equity for the present-value approach.

B. *Results Based on the Cash Flow Approach*

B.1. *Interest Expense, Interest Income, and ROA Betas*

We implement the income approach by estimating the interest sensitivity of banks' expense, interest income, and ROA to interest rate changes. We restrict the sample to banks that have at least 60 quarterly observations between 1984 and 2017 (15 years of data).[30] This yields a sample of 8,086 banks. We start with the analysis of the expense side by running the following time-series regression for each bank i:

$$\Delta IntExp_{it} = \alpha_i + \eta_t + \sum_{\tau=0}^{3} \beta_{i,\tau}^{Exp} \Delta FedFunds_{t-\tau} + \varepsilon_{it}, \tag{9}$$

where $\Delta IntExp_{it}$ is the change in bank i's interest expense rate from t to $t+1$, $\Delta FedFunds_t$ is the change in the Fed funds rate from t to $t+1$, α_i are bank fixed effects, and η_t are time fixed effects. The interest expense rate is total quarterly interest expense (total interest expense on deposits, wholesale funding, and other liabilities) divided by quarterly average assets and then annualized (multiplied by four). We allow for three lags of the Fed funds rate changes to capture the cumulative effect of Fed funds rate changes over a full year.[31] Our estimate of bank i's overall expense beta is the sum of the coefficients in (9), that is, $\beta_i^{Exp} = \sum_{\tau=0}^{3} \beta_{i,\tau}^{Exp}$. We estimate income and ROA betas by running analogous regressions to (9) for banks' interest income rate (total interest income divided by quarterly average assets) and ROA (net income divided by quarterly average assets) and summing up coefficients. In the case of ROA, it is necessary to adjust for seasonality due to the way loss provisions and other items are reported at the end of the year. We adjust for seasonality by averaging ROA over the current and prior three quarters before computing quarterly changes. We winsorize betas at the 5% level to minimize the impact of outliers.[32]

Finally, we calculate NIM betas as the difference between income betas and expense betas. Given the definition of NIM, this calculation is equivalent to estimating

[29] This is not just because banks do not mark all of their assets and liabilities to market prices. Rather, it is also because a large part of a bank's value—its deposit franchise—is not capitalized on the balance sheet.

[30] This follows the asset pricing literature, which generally requires 60 observations (five years of monthly data) to estimate betas with enough precision.

[31] We choose the one-year estimation window based on the impulse responses of interest income and interest expense rates to changes in the Fed funds rate. The impulse responses take about a year to build and then flatten out. Our results are robust to including more lags.

[32] In Section V.B.3 we show that our results do not depend on winsorization.

NIM betas from analogous regressions to (9). Overall, this estimation gives us a set of income betas, β_i^{Inc}, NIM betas, β_i^{NIM}, and ROA betas, β_i^{ROA}, in addition to the expense betas, β_i^{Exp}.

Figure 5 plots histograms of banks' interest expense betas (Panel A) and interest income betas (Panel B). The average expense beta is 0.345 and the average income beta is 0.351, which means that interest expense and interest income both rise by about 35 bps for every 100 bp increase in the Fed funds rate.[33] These numbers show that banks are on average well matched with income and expense betas that are almost identical. This finding mirrors our earlier result that the aggregate banking sector is well matched.

[Figure 5 about here]

Table I presents summary statistics on interest expense beta, interest income beta, NIM beta, and ROA beta for the full sample (Panel A) and the top 5% of banks by asset size (Panel B). Additional characteristics are averaged over time for each bank. As mentioned above, the average interest income and expense beta are almost identical. Thus, the difference between them, the NIM beta, is very close to zero at 0.006. The ROA beta is also close to zero at 0.032. This suggests that the average bank's cash flows are almost perfectly hedged to their interest rate risk, in terms of both NIM and ROA. The results are similar when we control for time fixed effects in the estimation.[34]

[Table I about here]

The table also presents a breakdown of bank characteristics by whether their expense beta is below or above the median. The average expense beta of the below-median group is 0.283 and that for the above-median group is 0.407. Low-expense-beta banks have significantly higher repricing maturity than high-expense-beta banks (3.8 years versus 3.4 years). This is not the case for liabilities (0.45 years versus 0.40 years). This result is consistent with the prediction that banks match their income and expense betas by adjusting the duration of their assets while keeping the duration of their liabilities overwhelmingly short. The variation in expense betas comes in part from the ratio of core deposits to total assets (0.76 versus 0.72). Yet most of the variation remains conditional on the core deposit ratio, which illustrates that banks differ in their ability to keep their deposit rates low and insensitive to the short rate. This result reflects differences in market power. NIM and ROA betas are close for both groups.

We find similar results when focusing on large banks in Panel B. The average expense and income beta are 0.417 and 0.433, respectively. The average NIM and

[33] The low average expense beta suggests that banks see a large increase in revenues from their liabilities when interest rates go up. The average size of the banking sector from 1984 to 2017 is \$7.768 trillion, which implies an increase in annual revenues of $(1\% - 0.345\%) \times \$7,768 = \$51$ billion per year from a 100 bp increase in the Fed funds rate. The revenue increase is large compared to the banking sector's average annual net income of \$70.2 billion over this period.

[34] In regressions with fixed effects, we estimate (9) as a panel regression and allow for different beta coefficients for each bank.

ROA beta are 0.015 and 0.039, respectively. These results show that the average large bank is also hedged to interest rate risk. Similar to the full sample, we find that the expense beta lines up with repricing maturity and the core deposit ratio and that NIM and ROA betas are close to zero for both groups.

We note that while the average NIM beta is close to zero, its cross-sectional standard deviation is positive, which suggests that some banks are not fully hedged with respect to interest rate risk. Some of the dispersion is likely due to estimation error. Note that income betas have a larger cross-sectional standard deviation than expense betas. This is explained by the fact that interest income is noisier than interest expense due to the more complex and heterogeneous nature of banks' assets compared to their liabilities (e.g., due to credit risk). This leads to greater estimation error in income and NIM betas than in expense betas. Consistent with estimation error, only 9.9% of NIM betas are statistically significantly different from zero when we would expect 5% to be so purely by chance. Also consistent with estimation error, we find no correlation between NIM betas and equity betas.[35] Fortunately, this estimation error does not affect our regression results because it enters on the left-hand side.

Estimation error aside, the variation in NIM betas is economically small. A bank at the 10th percentile has a NIM beta of -0.115. Such a bank is among the most exposed in the sample yet its NIM declines by just 11.5 bps per 100 bp increase in interest rates. This number is small compared to the average NIM of 312 bps. It is also small compared to the NIM beta implied by banks' duration mismatch, which is close to -1 (the NIM beta of the Treasury mimicking portfolio in Section II is -0.73). Hence, even the most exposed banks in our sample are several times less exposed than their duration mismatch would suggest.

It is also important to recognize that the variation across banks washes out in the aggregate. Opposite a bank at the 10th percentile of the NIM beta distribution is a bank at the 90th percentile whose NIM beta is 0.133. If there is a shock to interest rates, the effect on one bank will offset the effect on the other. The NIM of the aggregate banking sector is thus fully hedged, consistent with our aggregate analysis in Section II. In particular, if some banks experience a decline in capital due to an increase in interest rates, other banks will experience an increase in capital, leaving the aggregate banking sector as well capitalized as before. This is the relevant perspective for policy makers and regulators who focus on the risks of the system as a whole.

B.2. Cross-Sectional Analysis

In this section we formally test whether banks match the interest sensitivity of their income and expense using cross-sectional regressions. Our model predicts that income betas and expense betas should match one-for-one across banks. This quantitative prediction is unique to our theory, giving us a powerful empirical test.

[35] Internet Appendix Figure IA.4 presents a binned scatter plot of this relationship. The equity betas are discussed in Section V.C.

The top two panels of Figure 6 provide a graphical representation of the relationship between income and expense betas. Each panel shows a binned scatter plot that groups banks into 100 bins by expense beta and plots the average expense and income beta within each bin. The top left panel includes all banks, while the top right panel focuses on the largest 5% of banks by assets. While the full sample provides useful variation, the large banks are the economically important group, accounting for 83% of total assets.

[**Figure 6 about here**]

We find strong matching between income and expense betas: banks with low expense betas have low income betas and banks with high expense betas have high income betas. The magnitude of the relationship is close to one, as predicted by the model: the slope for all banks is 0.810 and the slope for large banks is 1.051. Thus, for the economically important large banks the prediction of the model holds almost exactly.

The raw correlations between expense and income betas are also very high: 52% for all banks and 61% for the large banks. Thus, the relationship is even tighter for large banks (the binned scatter plot looks noisier because it has 20 times fewer banks per bin). Expense betas thus explain a large amount of the variation in income betas across banks.

The bottom panels of Figure 6 examine bank profitability. We find that bank profitability is largely unexposed to interest rate changes. In particular, ROA betas are close to zero across the distribution of expense betas, for both all banks and large banks.[36] This is the case even though the matching coefficient for all banks was a bit below one. This indicates that non-interest items provide just the right offset to make profitability unexposed. The same result holds for large banks. Thus, the tight matching of interest expense and income betas effectively insulates bank profitability from interest rate changes.

Next, we examine matching using OLS regressions. Specifically, we estimate the beta-on-beta regression

$$\beta_i^{Inc} = \alpha + \gamma \beta_i^{Exp} + \epsilon_i, \tag{10}$$

where β_i^{Inc} is the interest income beta of bank i, β_i^{Exp} is the interest expense beta of bank i, and α is a constant. Our theory predicts that the matching coefficient γ is close to 1.

We note that we need to correct the standard errors for the fact that the betas themselves are estimated. We address this issue by using a block bootstrap. In a block bootstrap, samples of data are generated by drawing blocks of the data with replacement. Sampling the data in blocks gives the generated samples the same correlation structure (within a block) as in the data. We take a block to be the cross-section of banks in a given quarter, thereby capturing the cross-sectional correlations

[36] Results for NIM betas are similar due to the close matching between income and expense betas (see Internet Appendix Figure IA.3). We focus on ROA betas because they contain additional information from non-interest income and expenses.

within a quarter. We estimate the betas and the beta-on-beta regression for each generated sample. We use the distribution of the coefficients from the beta-on-beta regression across samples to construct the standard error.

Table II presents the beta-on-beta regression results. Columns (1) and (2) use betas with and without time fixed effects for the full sample of banks. The matching coefficients, 0.810 and 0.806, respectively, are similar and fairly close to one.[37] These results show that the matching is not driven by some type of common time-series variation. The constant is small with a coefficient of 0.072, which indicates that a bank with zero interest expense sensitivity has near-zero interest income sensitivity.

[**Table II about here**]

Columns (3) to (8) report results for the largest 10%, 5%, and 1% of banks. Here the coefficients without controlling for time fixed effects are almost exactly one, at 1.065 for the top 10%, 1.051 for the top 5%, and 0.956 for the top 1%. All of the estimates are within 1.5 standard errors of one, and thus we cannot reject the strong hypothesis of one-for-one matching. This is despite the fact that the bootstrapped standard errors are quite small. The high statistical power allows us to provide a fairly precise estimate even for the subsamples of the largest 5% and 1% of banks. Moreover, the coefficients are almost unchanged when we include time fixed effects. The direct effect of Fed funds rate changes is small and insignificant, which indicates that a bank with insensitive interest expense is expected to have insensitive interest income, that is, to hold only long-term fixed-rate assets.

Extrapolating from these estimates, a bank whose interest expense rises one-for-one with the Fed funds rate is predicted to hold only short-term assets. This describes money market funds, which obtain funding at rates close to the short rate and do not engage in maturity transformation. The ability of our estimates to capture the behavior of money market funds out of sample shows a high degree of external validity.

Figure 7 takes a closer look at matching across the distribution of bank size. Specifically, it shows a binned scatter plot of income and expense betas against log assets (averaged for each bank over time). Both income and expense betas are increasing in bank size: small banks have income and expense betas of around 0.3 while the largest banks have betas around 0.45. This makes sense as large banks rely more heavily on wholesale funding, which has an expense beta of one. The important result of the figure is that large banks match their higher expense betas one-for-one with higher income betas. As the fitted lines in the scatter plot show, income and expense betas increase almost exactly in parallel across the size distribution. In fact, the ratio of their slopes, which measures the matching coefficient γ, is 1.02. Thus, one-for-one sensitivity matching holds strongly across the full distribution of bank size.

[**Figure 7 about here**]

[37] A coefficient of 0.810 implies that an analogous regression of NIM betas on expense betas has a coefficient of $0.810-1=-0.190$. This is indeed what we find, as reported in Internet Appendix Table IA.VII.

Table III presents results for the interest sensitivity of banks' ROA. We estimate regression (10) after replacing the interest income beta with the ROA beta. The coefficients are close to zero and statistically insignificant across all subsamples. They are unchanged when we include time fixed effects in the beta estimation. These results imply that non-interest income and expenses are largely insensitive to interest rate changes, consistent with our model.[38]

[Table III about here]

Taken together, Tables II and III provide strong evidence that banks match the interest rate sensitivities of their income and expense one-for-one. This holds despite the fact that there is large cross-sectional variation in each of these sensitivities. As a consequence of this matching, banks' profitability is largely insulated from interest rate changes.

B.3. Panel Analysis

In this section we run panel regressions that impose a slightly more stringent test of sensitivity matching than the cross-sectional regressions in Section B.2. Specifically, we run the following two-stage procedure:

$$\Delta IntExp_{i,t} = \alpha_i + \eta_t + \sum_{\tau=0}^{3} \beta_{i,\tau}^{Exp} \Delta FedFunds_{t-\tau} + \varepsilon_{i,t} \tag{11}$$

$$\Delta IntInc_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_\tau \Delta FedFunds_{t-\tau} + \delta \Delta \widehat{IntExp}_{i,t} + \varepsilon_{i,t}. \tag{12}$$

The first stage is identical to (9). The difference is in the second stage. Whereas in (10) we run a cross-sectional regression of income betas on expense betas, in (12) we run a panel regression of interest income on the *fitted value* of interest expense from the first stage, $\Delta\widehat{IntExp}_{i,t}$. The resulting coefficient δ is analogous to γ in (10). A δ close to one shows that banks match variation in their interest expense induced by Fed funds rate changes one-for-one with variation in their interest income. Conversely, the coefficients γ_τ give us the direct effect of Fed funds rate changes on interest income, independent of interest expense, and hence they are analogous to the constant α in the cross-sectional regression (10). In some specifications we replace this direct effect with time fixed effects to ensure that it does not affect our matching coefficient δ.

The main difference between the two procedures is that while the cross-sectional regression sums the lag coefficients $\beta_{i,\tau}^{Exp}$ for each bank, in the panel regression they enter separately. Thus, the panel regression tests whether banks match the sensitivities of interest income and expense lag-by-lag, not just on average across all four lags. This is the sense in which the panel regression imposes a more stringent test.[39]

[38] In the robustness tests reported in Section V.D, we show directly that the main categories of banks' operating costs are insensitive to interest rate changes.

[39] We formalize this argument in Section X of the Internet Appendix, where we also present panel analogs to all of our cross-sectional matching regressions. The results are similar in all cases.

Notice also that the panel regression naturally weights banks by their number of observations, and hence it is no longer necessary to impose a filter on this number or to winsorize the betas to reduce measurement error. Thus, the panel regression also provides robustness for our main results.

Table IV presents the panel regression results, presented analogously to Table II and III. In addition, even-numbered columns show the combined direct effect $\sum_0^3 \gamma_\tau$ of Fed funds rate changes, while odd-numbered columns replace it with time fixed effects. Standard errors are block-bootstrapped as before.

[Table IV about here]

From Panel A columns (1) and (2), the coefficient estimates for the full sample of banks are 0.886 and 0.887 in the specifications with a direct effect and time fixed effects, respectively. These numbers are very similar to those in the cross-sectional regression and very close to one. The direct effect of Fed funds rate changes in column (1) is small, and thus a bank with no interest expense exposure is predicted to have no interest income exposure either, that is, to hold only long-term fixed-rate assets.

Columns (3) to (8) show similar results for the largest 10%, 5%, and 1% of banks. The coefficients are again similar to those in Table II and very close to one both statistically and in terms of magnitude. The results are almost unchanged when we include time fixed effects. The direct effect of Fed funds rate changes is again small and insignificant, and thus our results extrapolate well to money market funds.

Panel B of Table IV presents the results for ROA. We use the same two-stage procedure but replace the change in interest income in equation (12) with the change in ROA. The resulting coefficients are very close to zero across all columns. They are unchanged regardless of whether we include the direct effect of Fed funds rate changes (odd-numbered columns) or time fixed effects (even-numbered columns). These results confirm those of the cross-sectional regressions in Table III by showing that non-interest items do not undo the matching of interest income and expense sensitivities. This leaves banks' bottom lines unexposed to interest rate shocks.

Taken together, the panel regression results in Tables II and III strengthen the evidence of one-for-one matching by showing that it holds lag-by-lag and is robust to different specifications.

C. Results Based on the Present-Value Approach

We complement the result based on the income approach using the present-value approach. The present-value approach tests for matching by examining the effect of interest rates on the market value of bank equity. To implement this approach, we obtain the daily stock returns of all publicly listed banks and use them to compute FOMC betas as in Figure 2.[40] Specifically, we regress each bank's stock return on the change in the one-year Treasury rate over a one-day window around scheduled FOMC announcements between January 1994 and June 2007. We then merge the

[40] We thank Anna Kovner for providing the list of publicly listed banks. The analysis is at the level of the bank holding company because banks are publicly listed through their holding company.

FOMC betas with the interest expense and income betas. The merged sample contains 597 publicly listed banks. The average FOMC beta is −2.10, which is similar to the industry-level FOMC beta in Figure 2.

Figure 8 presents binned scatter plots of FOMC betas against interest expense and income betas, and against the repricing maturities of assets and liabilities (a rough proxy for duration). While the relationships are noisy due to the high volatility of stock returns, the standard errors are small enough to detect meaningful effects. For instance, given banks' ten-to-one leverage, under the standard duration calculation FOMC betas should decline by 10 for every additional year of asset duration.

[Figure 8 about here]

Contrary to this prediction, the relationship between FOMC betas and all four sorting variables is flat. If anything, FOMC betas rise toward zero as repricing maturity increases and income betas fall, but the effects are small and insignificant.[41] Figure 8 thus confirms our results for NIM and ROA, which show that interest rate exposure is equally low throughout the distribution of banks. This result is consistent with our framework where banks are able to avoid interest rate risk by matching the sensitivities of their income and expense. Thus, the present-value approach confirms the results of the cash flow approach.

D. Robustness

Operating costs and fee income. In our model banks' operating costs are insensitive to interest rate changes and therefore resemble a long-term fixed-rate liability. As we note above, the results in Figure 6 and Tables II and III are consistent with this assumption. Here we provide direct evidence for it by analyzing the interest rate sensitivity of the main components of banks' non-interest expense and income.

Banks have substantial operating expense and fee income. We analyze the six main categories: salaries, rent, deposit fee income, total non-interest income, loan loss provisions, and trading income. For each category, we estimate interest rate betas as in equation (9).

The results are presented as binned scatter plots in Internet Appendix Figure IA.2 and are constructed in the same manner as Figure 6. The figure shows that for all categories, the betas are close to zero for both the full sample and the largest 5% of banks. Moreover, they exhibit no correlation with banks' interest expense betas. These findings show that non-interest income and expense are largely insensitive to changes in interest rates, consistent with the model.

Interest rate derivatives. Banks can use interest rate derivatives to hedge their assets. In doing so, they would be giving up the term premium (essentially, whoever is on the other side would be the one engaging in maturity transformation). While our matching results imply that there is no need to do so, it is useful to look at derivatives hedging directly.

[41] English, Van den Heuvel, and Zakrajšek (2018) similarly find that banks with a larger maturity gap have a dampened exposure to monetary policy.

The Call Reports contain information on the notional amounts of derivatives used for non-trading (e.g., hedging) purposes since 1995. They do not, however, contain information on the direction and term of the derivatives contracts, making it impossible to precisely calculate exposures. We therefore take the simple approach of rerunning our matching tests separately for banks that do and do not use interest rate derivatives.

Consistent with prior studies (e.g., Purnanandam (2007), Rampini, Viswanathan, and Vuillemey (2020)), we find that the large majority of banks (74%) do not use any interest rate derivatives. This is not surprising under our framework because banks do not need derivatives to hedge.

Internet Appendix Table IA.IV presents the regression results. Columns (1) and (2) include all banks with nonmissing derivatives amounts since 1995. The matching coefficients are similar to those reported for the full sample in Table II. Columns (3) and (4) show nearly identical coefficients for banks with zero derivatives amounts as for the full sample. The coefficients for banks using derivatives in columns (5) and (6) are higher and close to one. This is due to the fact that larger banks are more likely to use interest rate derivatives and the matching coefficient for large banks in Table II is close to one. Overall, the results are consistent for banks that use derivatives and banks that do not.

Asymmetry. We examine whether there is asymmetry in banks' responses to Fed funds rate increases and decreases.[42] We do so by allowing for separate betas for Fed funds rate increases and decreases in the cross-sectional analysis described in Section V.B.2. Internet Appendix Table IA.V reports the coefficients. We find that banks are slightly faster to reduce than to raise interest expense during the six months after a Fed funds rate change. However, this effect disappears when considering the impact of Fed funds rate changes over a one-year horizon. The cumulative one-year change in interest expense for Fed funds rate increases and decreases is almost identical at 37 bps and 34 bps, respectively. Thus, there is no asymmetry when considering the cumulative adjustment over a one-year period.[43]

The short delay has a negligible effect on bank profitability. The coefficients in Internet Appendix Table IA.V imply that the increase in bank profits during the first year of a 100 bp change is only 3 bps higher for a Fed funds rate increase relative to a decrease. The difference is even smaller for Fed funds rate changes that go beyond one year because the asymmetry only affects profitability during the first year. Given that the Fed funds rate is highly persistent, this implies that asymmetry has a limited effect on bank profitability and on our main matching results. The first-order effect of Fed funds rate changes on bank profitability is due to the partial adjustment of deposit rates to the Fed funds rate, that is, it comes from the fact that expense betas are far less than one.

[42] Neumark and Sharpe (1992) find evidence of an asymmetric response of deposit rates using data from the 1980s. Kahn, Pennacchi, and Sopranzetti (2005) find an asymmetric response for personal loans and car loans using data from the 1990s.

[43] Yankov (2014) finds a similarly small and short-lived (four-week) asymmetry in the response of deposit rates to Fed funds rate changes.

Bank holding companies. Our main analysis uses commercial bank data from the Call Reports. As a simple robustness check, we rerun Table II using regulatory data at the bank holding company level, which is available since 1986. Internet Appendix Table IA.VI presents the results. The matching coefficients are very close to one. The results hold for the full sample, the top 10%, the top 5%, and even the top 1% of bank holding companies. Hence, our matching results are independent of whether we use commercial bank data or bank holding company data.

VI. Interest Rate Risk Hedging and Bank Assets

In this section we examine how banks implement interest sensitivity matching by looking at the composition of their assets.

A. Asset Duration

Our model predicts that banks with low expense betas can implement sensitivity matching by holding assets with higher duration. We test this prediction using repricing maturity as a rough proxy for duration.[44] The left panel of Figure 9 shows a binned scatter plot of the average repricing maturity of banks' loans and securities against their interest expense betas. The relationship is strongly downward-sloping. Hence, as predicted by the model, banks with low expense betas hold assets with substantially higher duration than banks with high expense betas. The slope of the relationship is −4.5 years, which is on the order of the average repricing maturity of bank assets. As a result, a bank with an expense beta of 0.1 has a predicted repricing maturity of 4.8 years, while a bank with an expense beta of one is predicted to have a repricing maturity of just 0.7 years. This again describes the structure of money market funds, which are not in our sample but are nevertheless in line with our estimates.[45]

[Figure 9 about here]

The right panel in Figure 9 looks at a related measure, banks' share of short-term assets, defined as those that reprice within a year. As predicted by the model, there is a significant positive relationship: banks with high expense betas have more short-term assets than banks with low expense betas (the slope is 0.530). Overall, Figure 9 shows that expense betas explain large differences in maturity transformation across banks.

We provide a formal test of the relationship between expense betas and repricing

[44] We calculate the repricing maturity of bank assets as the weighted average of the repricing maturities of bank loans, securities, and short-term instruments. For securities and loans, we have detailed repricing maturity going back to 1997. For short-term instruments (cash, Fed funds sold, and securities bought under agreement to resell), we impute a repricing maturity of zero.

[45] Money market funds hold only very short-term assets. Kacperczyk and Schnabl (2013) estimate that assets held by prime money market funds have an average maturity of 34 days.

maturity by running panel regressions of the form

$$RepricingMaturity_i = \quad \alpha + \delta \beta_i^{Exp} + \gamma X_i + \epsilon_i, \tag{13}$$

where $RepricingMaturity_i$ is the average repricing maturity of bank i's loans and securities, β_i^{Exp} is its interest expense beta, and X_i comprises a set of controls. The controls we consider are average wholesale funding share (large time deposits plus Fed funds purchased and repo), the equity ratio, and the natural logarithm assets. As before, we block-bootstrap the standard errors by quarter with 1,000 iterations.

Panel A of Table V presents the regression results for the sample of all banks. From column (1), the univariate coefficient on the interest expense beta is −4.508. The coefficient is statistically significant at the 1% level. The coefficient remains stable and actually increases slightly as we add the control variables in columns (2) to (4). Column (5) runs a horse race between all right-hand-side variables. The coefficient on the interest expense beta is −6.520, and thus its explanatory power for repricing maturity is even stronger once we control for bank characteristics.

[Table V about here]

Panel B of Table V repeats this analysis for the largest 5% of banks. Even though this sample has only 266 banks (and bootstrapped standard errors), the relationship between interest expense betas and repricing maturity is strong. We find that the univariate coefficient is −6.465, which is even slightly larger than the full sample. The effect rises to −7.389 in the specification with all controls (column (5)). This estimate, which applies to large banks, suggests that the aggregate banking sector would not engage in any maturity transformation if its interest expense were to rise one-for-one with the short rate.

B. Asset Composition

We can get a better understanding of how banks obtain duration by looking at the composition of their assets. Internet Appendix Table IA.III summarizes the repricing maturity of different asset categories. It shows that the main way banks obtain duration is by investing in securities, which in aggregate have an average repricing maturity of 8.4 years versus 3.8 years for loans.[46] Given these large differences, and given our results so far, we expect banks with low expense betas to hold a larger share of securities.

Table VI presents the results of regressions similar to (13) but with banks' securities share as the dependent variable. Looking first at the sample of all banks in Panel A, there is a strong and significant negative relationship between interest expense beta and the securities share. The stand-alone coefficient in column (1) is −0.322 while the multivariate coefficient in column (5) is −0.127. These numbers are large relative to the average securities share in Table I, which is 0.275, and their sign is as

[46] This is explained by the fact that most securities held by banks are backed by mortgages, which tend to be long-term and fixed-rate.

predicted. Panel B repeats the analysis for the largest 5% of banks. The coefficients are −0.243 in column (1) and −0.239 in column (5), again highly significant. By contrast, except for size, the control variables either lose their significance or see their signs flip. Thus, we find robust evidence of a negative relationship between interest expense betas and banks' securities holdings, which indicates that banks with low expense betas obtain duration by holding more securities.[47]

[Table VI about here]

This result is especially useful because it allows us to rule out an alternative explanation for our sensitivity matching results. It is possible that banks with high expense betas face more liquidity (or run) risk. Combined with the assumption that short-term assets act as a liquidity buffer, this could explain why banks with high expense betas hold assets with lower duration (though it does not necessarily predict one-for-one matching). However, under this explanation these banks should hold more securities because securities are liquid and can be sold easily during a run, unlike loans. The fact that we see the opposite—high-expense-beta banks hold fewer securities—indicates that liquidity risk does not drive our results.

C. Hedging within the Securities Portfolio

Our model predicts that banks actively match the interest sensitivities of their income and expense in order to manage their interest rate risk. Yet another possibility is that the matching is incidental. For instance, it may arise from market segmentation if banks with more market power over deposits also happen to face more long-term lending opportunities. Along these lines, Scharfstein and Sunderam (2016) find that banks have market power over lending. Although market segmentation does not explain why we see one-for-one matching, we nevertheless test it further.

We do so by looking at the interest rate sensitivity of banks' securities holdings. Unlike loans, securities are traded in an open market and hence are unaffected by market segmentation. Thus, under the market segmentation interpretation we should not see matching between banks' expense betas and the income betas of their securities holdings. To implement this idea, we rerun our main matching test based on equation (10) but with the securities beta as the outcome variable. The securities beta is computed based on equation (10) with the change in the securities interest rate as outcome variable. While we no longer expect a coefficient of one (one-for-one matching applies only to the bank as a whole), our model still predicts positive matching between expense betas and securities income betas.

Panel A of Table VII presents the results for the sample of all banks. As columns (1) and (2) show, there is strong evidence of matching between securities interest expense beta. The coefficients are 0.266 and 0.259, respectively, and highly significant. Columns (3) to (8) look at various subcategories of securities. Since banks sometimes retain some self-originated securities, we get a cleaner test by looking only at

[47] Replacing securities' share with loans' share of assets yields an almost identical coefficient but with the opposite sign. This is not surprising given that securities and loans account for 84% of bank assets.

Treasury securities and agency MBS, which are among the most liquid securities in existence. Columns (3) and (4) show that there is matching even within this category. Columns (5) to (8) find the same for MBS and other securities. Panel B of Table VII repeats the analysis for the largest 5% of banks. The results are qualitatively the same. The matching coefficients are somewhat larger across the board, suggesting that large banks are even more likely to match the sensitivity of their interest expense using securities. Overall, the results in Table VII support the view that banks actively match the interest rate exposures of their income and expense.

[Table VII about here]

VII. Market Power and Bank Interest Rate Risk

Our model predicts that banks with more market power in retail deposit markets have lower interest expense betas, which they match with lower interest income betas. We use geographic variation in market power to test these predictions. Specifically, we first examine whether variation in market power generates differences in expense betas. We then examine whether banks match these differences with their income betas.

We use three sources of geographic variation in market power that are progressively more restrictive. We embed each source within the same empirical framework used in Section V. Specifically, we run the following instrumental variables regression:

$$\begin{aligned} \beta_i^{Exp} &= \alpha + \gamma MP_i + \epsilon_i \quad \text{[Stage 1]} \\ \beta_i^{Inc} &= \alpha + \delta \widehat{\beta_i^{Exp}} + \epsilon_i, \quad \text{[Stage 2]} \end{aligned}$$

where MP_i is bank i's market power, $\Delta IntExp_{i,t}$, β_i^{Inc}, and β_i^{Exp} are estimated according to (9), and $\widehat{\beta_i^{Exp}}$ is the predicted interest expense beta from the first stage. The difference relative to the earlier regressions is that we now parameterize the interest expense rate as a function of a given proxy for market power, $MP_{i,t}$. In the first stage, we are interested in the relationship between market power and the interest expense rate. In the second stage, we are interested in the matching coefficient δ.

One advantage of the instrumental variables approach is that it helps check for attenuation bias that could arise from estimation error in our expense betas. As noted in Section V.A, estimation error is more of a concern for income betas than expense betas since interest income is much noisier than interest expense. Nevertheless, if expense betas also suffer from significant estimation error, then the matching coefficient in the instrumental variables regression should be higher than the OLS matching coefficients. This provides a useful check.

The instrumental variables approach also helps us identify the causal effect of β^{Exp} on β^{Inc} under the assumption that market power only affects β^{Inc} through its effect on β^{Exp}. We think this assumption is plausible given the result in Section VI.C that matching extends to the securities portfolio and hence is not driven by local loan demand conditions that might correlate with market power. In addition, branch networks are highly persistent while asset duration is easily adjusted, which argues against reverse causality. That said, it is certainly possible that banks with more long-term assets (low β^{Inc}) choose to locate their branches in areas where they have a lot of market power (high MP), which in turn would lower their interest expense sensitivity (low β^{Exp}). Note, however, that this interpretation still supports our main conclusion that banks hedge interest rate risk by carefully matching the interest rate risk of their assets and liabilities.

A. *Market Concentration*

Our first source of variation in market power is local market concentration. We use the FDIC data to calculate a Herfindahl-Hirschman index (HHI) for each U.S. county by computing each bank's share of the total branches in the county and summing the squared shares. We then create a bank-level HHI by averaging the county HHIs of each bank's branches, using the bank's branches presence in each county as weights. To reduce the impact of outliers we winsorize the bank HHIs at the 5% level. The bank HHIs have a mean of 0.191 and a standard deviation of 0.117, indicating substantial geographic variation.

Figure 10 shows that there is a negative relationship between market concentration and interest expense betas. Banks operating in counties with an HHI of zero have an average interest expense beta of 0.34 versus 0.3 for those in counties with an HHI of 0.45. Note that even though there is substantial variation, interest expense betas are well below one everywhere. Thus, banks appear to have significant market power in all areas, which allows them to justify the high costs of operating a deposit franchise.

[Figure 10 about here]

The first two columns of Table VIII present the results of the first stage. The first-stage estimates in the top panel show that market concentration is significantly negatively related to the interest expense beta, as predicted. The first-stage coefficient in column (1) is -0.092, which is the same as the slope of the fitted line in Figure 10. The coefficient is almost unchanged (-0.094) when we control for time fixed effects in the beta estimation in column (2).

[Table VIII about here]

The second two columns of Table VIII show that the variation in interest expense beta induced by market concentration is matched on the income side. The second-stage coefficients are 0.917 and 0.953 in columns (1) and (2), respectively, which are again quite close to one (both are within a standard error of one statistically). Thus, the results in Table VIII support the market power mechanism of our model and its sensitivity matching prediction. Moreover, the fact that the second-stage coefficients do not exceed those in Table IV suggests that attenuation bias due to estimation error in expense betas is not a significant concern.

B. Retail Deposit Betas

Banks in our model derive market power from the retail deposits they sell to households. In this section we use data on retail deposits to obtain variation in market power. We use Ratewatch data and restrict the sample counties with at least 60 non-missing observations from 1997 to 2008. Because retail deposits are government-insured and hence immune to runs, they also allow us to further show that our results are not explained by liquidity risk.

The Ratewatch data contain the rates offered on new accounts of different retail deposit products at branches throughout the U.S. To obtain variation in market power, we regress these rates on the Fed funds rate, allowing for separate coefficients by county,

$$DepRate_{b,i,c,t} = \alpha_b + \gamma_i + \delta_c + \eta_t + \sum_c \beta_c \times FedFunds_t + \varepsilon_{b,i,c,t}, \tag{14}$$

where $DepRate_{b,i,c,t}$ is the deposit rate of branch b of bank i in county c on date t. We run (14) separately for the three most common products in our data: interest checking accounts with less than \$2,500, \$25,000 money market deposit accounts, and \$10,000 12-month CDs. These products are representative of the three main types of retail (core) deposits: checking, savings, and small time deposits. They are also well below the deposit insurance limit.

The county-level coefficients β_c are the counterpart to the market power parameter β^{Exp} in the model. By capturing the sensitivities of local deposit rates to the Fed funds rate, they provide a measure of local market power. We use them to construct a bank-level measure by averaging them across each bank's branches (using branch deposits as weights), and finally by averaging across the three products for each bank.

The first four column of Table IX present the results. The first-stage coefficients in columns (1) and (2) are highly significant and equal to 0.510 and 0.514, respectively. This shows that retail deposit betas strongly predict banks' interest expense betas.

[Table IX about here]

The second-stage estimates in columns (3) and (4) show the matching. The coefficients are 0.939 and 0.943, respectively, which is very close to one both in magnitude and statistically (within one standard error). This result again helps rule out significant attenuation bias in our main results, as well as confirms that banks match variation in retail deposit betas one-for-one with their interest income sensitivities.

As our third source of variation in market power, we go a step further and isolate within-bank variation in retail deposit betas. We do so by including bank-time fixed effects in the estimation of the retail deposit betas (equation (14)). The resulting estimates are identified by comparing branches of the same bank located in different areas. This purges the retail deposit betas of any time-varying bank-level characteristics so that they capture only differences in local market power.

The results are presented in the last four columns of Table IX. As the first-stage estimates in columns (5) and (6) show, the within-bank retail deposit betas have a significant and sizable impact on banks' interest expense betas. This is true even though they are constructed in a way that ignores all bank-level variation in deposit rates across banks and only use variation within banks.

The second-stage estimates show that variation in within-bank retail deposit betas also produces strong matching between interest expense and interest income sensitivities. The matching coefficients are 0.834 and 0.841 in columns (7) and (8), which is again close to one both statistically and in terms of in magnitude, and also helps rule out attenuation bias in our main results. Overall, Table IX confirms the prediction that differences in market power induce variation in expense betas that banks match one-for-one on the income side.

VIII. Conclusion

The conventional view holds that by borrowing short and lending long, banks expose their bottom lines to interest rate risk. We argue that the opposite is true: banks reduce their interest rate risk through maturity transformation. They do so by matching the interest rate sensitivities of their income and expense even as they maintain a large maturity mismatch. On the expense side, banks obtain a low sensitivity by exercising market power in retail deposit markets. On the income side, they obtain a low sensitivity by holding long-term fixed-rate assets. This sensitivity matching produces stable net interest margins (NIM) and return on assets (ROA) even as interest rates fluctuate widely.

Our results have important implications for monetary policy and financial stability. Monetary policy is thought to impact banks in part through the interest rate risk exposure created by their maturity mismatch. Our results show that by actively matching the sensitivities of their income and expense, banks are largely insulated from this effect. Banks' maturity mismatch is also a source of concern about financial stability. This has led to calls for narrow banking, the idea being that deposit-issuing institutions should hold only short-term assets. Our results imply that as long as banks have market power, narrow banking could actually expose them to greater risk.

More broadly, our results provide an explanation for why deposit-taking and maturity transformation co-exist under one roof. Rather than viewing such co-existence as a source of risk and instability, this explanation highlights its contribution to stability.

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Supporting Information

Additional Supporting Information may be found at Philipp Schnabl's website:

Internet Appendix.
Replication Kit.

Table I

Bank Characteristics and Expense Beta

This table provides summary statistics on bank characteristics. The sample for Panel A is all U.S. commercial banks with at least 60 quarterly observations from 1984 to 2017 (8,086 banks). Panel B restricts the sample to the largest 5% of banks (404 banks). Interest expense betas are calculated by regressing the change in a bank's interest expense rate on the contemporaneous and three previous quarterly changes in the Fed funds rate and summing the coefficients (see equation (9) in the main text). Interest income and return on assets betas are calculated analogously. The net interest margin beta is the difference between interest income and interest expense betas. Betas are winsorized at the 5% level. Time FE denotes whether time fixed effects are included in the estimation of betas. The data on repricing maturities starts in 1997. Columns (1) and (2) report the sample mean and standard deviation, respectively. Columns (3) and (4) report averages for banks with above- and below-median interest expense beta.

Panel A: All banks				
	All		Low beta	High beta
	Mean (1)	St. Dev. (2)	Mean (3)	Mean (4)
Interest rate sensitivity				
Interest expense beta	0.345	(0.077)	0.283	0.407
Interest income beta	0.351	(0.120)	0.302	0.400
ROA beta	0.032	(0.107)	0.032	0.032
NIM beta	0.006	(0.103)	0.019	−0.007
Interest expense beta (Time FE)	0.334	(0.076)	0.273	0.394
Interest income beta (Time FE)	0.340	(0.119)	0.292	0.388
ROA beta (Time FE)	0.032	(0.106)	0.031	0.033
NIM beta (Time FE)	0.006	(0.103)	0.019	−0.007
Bank characteristics				
Asset repricing maturity	3.592	(1.569)	3.820	3.365
Liabilities repricing maturity	0.426	(0.202)	0.448	0.403
Log avg. assets	4.634	(1.291)	4.328	4.940
Loans/Assets	0.569	(0.119)	0.548	0.589
Securities/Assets	0.275	(0.120)	0.295	0.255
Core deposits/Assets	0.737	(0.091)	0.758	0.716
Equity/Assets	0.102	(0.032)	0.107	0.097
Observations	8,086	8,086	4,043	4,043

Table I—*continued.*

Panel B: Top 5% of banks				
	All		Low beta	High beta
	Mean (1)	St. Dev. (2)	Mean (3)	Mean (4)
Interest rate sensitivity				
Interest expense beta	0.417	(0.078)	0.353	0.482
Interest income beta	0.433	(0.133)	0.363	0.502
ROA beta	0.039	(0.118)	0.048	0.031
NIM beta	0.015	(0.105)	0.010	0.021
Interest expense beta (Time FE)	0.406	(0.077)	0.344	0.468
Interest income beta (Time FE)	0.421	(0.132)	0.352	0.489
ROA beta (Time FE)	0.040	(0.116)	0.046	0.034
NIM beta (Time FE)	0.015	(0.105)	0.008	0.022
Bank characteristics				
Asset repricing maturity	3.905	(1.801)	4.497	3.313
Liabilities repricing maturity	0.383	(0.281)	0.375	0.390
Log avg. assets	8.135	(1.263)	7.903	8.367
Loans/Assets	0.609	(0.118)	0.609	0.610
Securities/Assets	0.222	(0.107)	0.243	0.201
Core deposits/Assets	0.622	(0.177)	0.683	0.562
Equity/Assets	0.095	(0.039)	0.094	0.096
Observations	404	404	202	202

Table II

Interest Sensitivity Matching

This table provides estimates of the matching of interest income and expense sensitivities. The data are quarterly and cover all U.S. commercial banks with at least 60 observations from 1984 to 2017. The interest expense beta and income beta are calculated according to equation (9) in the main text and winsorized at the 5% level. We estimate the OLS regression

$$\beta_i^{Inc} = \alpha + \gamma \beta_i^{Exp} + \epsilon_i,$$

where β_i^{Inc} and β_i^{Exp} are bank i's income and expense beta, respectively. Top 10% are the largest 10% of banks by average inflationadjusted assets over the sample. Top 5% and top 1% are defined analogously. Time FE denotes whether time fixed effects are included in the estimation of income and expense betas. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Int. exp. beta	0.810***	0.806***	1.065***	1.074***	1.051***	1.054***	0.956***	1.007***
	(0.039)	(0.037)	(0.057)	(0.057)	(0.076)	(0.077)	(0.176)	(0.186)
Constant	0.072***	0.071***	−0.012	−0.015	−0.006	−0.007	0.021	−0.003
	(0.021)	(0.021)	(0.028)	(0.027)	(0.037)	(0.037)	(0.082)	(0.084)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of banks	8,086	8,086	808	808	404	404	80	80
R^2	0.271	0.266	0.416	0.416	0.377	0.372	0.251	0.254

Table III

Interest Sensitivity of Return on Assets (ROA)

This table provides estimates of the interest rate sensitivity of ROA. The data are quarterly and cover all U.S. commercial banks with at least 60 observations from 1984 to 2017. The interest expense beta and ROA beta are calculated according to equation (9) in the main text and winsorized at the 5% level. We estimate the OLS regression

$$\beta_i^{ROA} = \alpha + \gamma \beta_i^{Exp} + \epsilon_i,$$

where β_i^{ROA} and β_i^{Exp} are bank i's ROA and expense beta, respectively. Top 10% are the largest 10% of banks by average inflationadjusted assets over the sample. Top 5% and top 1% are defined analogously. Time FE denotes whether time fixed effects are included in the estimation of ROA and expense betas. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Int. exp. beta	0.002	0.014	−0.038	0.018	−0.107	−0.049	−0.105	−0.034
	(0.030)	(0.030)	(0.065)	(0.048)	(0.079)	(0.063)	(0.144)	(0.144)
Constant	0.031***	0.027***	0.058***	0.036*	0.084***	0.060*	0.072	0.041
	(0.015)	(0.012)	(0.038)	(0.029)	(0.045)	(0.037)	(0.074)	(0.070)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of banks	8,086	8,086	808	808	404	404	80	80
R^2	< 0.0001	0.0001	0.0007	0.0002	0.0049	0.0010	0.0041	0.0004

Table IV

Interest Sensitivity Matching: Panel Estimation

This table provides estimates of the matching of interest income, ROA, and expense sensitivities to Fed funds rate changes. The results are from the two-stage ordinary least squares regression

$$
\begin{aligned}
\Delta IntExp_{i,t} &= \alpha_i + \eta_t + \textstyle\sum_{\tau=0}^{3} \beta_{i,\tau} \Delta FedFunds_{t-\tau} + \epsilon_{i,t} && \text{[Stage 1]} \\
\Delta Rate_{i,t} &= \lambda_i + \textstyle\sum_{\tau=0}^{3} \gamma_\tau \Delta FedFunds_{t-\tau} + \delta \Delta \widehat{IntExp}_{i,t} + \varepsilon_{i,t}, && \text{[Stage 2]}
\end{aligned}
$$

where $\Delta IntExp_{i,t}$ is the change in the interest expense rate of bank i at time t, $\Delta Rate_{i,t}$ is the change in the interest income rate in Panel A or the change in ROA in Panel B, $\Delta FedFunds_t$ is the change in the Fed funds rate, and $\Delta \widehat{IntExp}_{i,t}$ is the predicted value from the first stage. Columns (2), (4), (6), and (8) include time fixed effects in place of $\sum_{\tau=0}^{3} \gamma_\tau \Delta FedFunds_{t-\tau}$. Top 10% are the 10% largest banks by average total assets over the sample. Top 5% and top 1% are defined analogously. The data are quarterly and cover all U.S. commercial banks from 1984 to 2017. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

Panel A: Δ Interest income rate

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \widehat{IntExp}$	0.886***	0.887***	1.116***	1.119***	1.139***	1.141***	0.888***	0.898***
	(0.031)	(0.031)	(0.073)	(0.074)	(0.082)	(0.084)	(0.163)	(0.163)
$\sum \gamma_\tau$	0.051		−0.046		−0.070		0.017	
	(0.019)		(0.036)		(0.043)		(0.085)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	1,168,863	1,168,863	109,170	109,170	52,418	52,418	10,661	10,661
No. of banks	18,467	18,467	1,843	1,843	917	917	184	184
R^2	0.097	0.126	0.120	0.145	0.131	0.157	0.123	0.158

Panel B: Δ ROA

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \widehat{IntExp}$	0.060	0.079	−0.013	0.002	−0.031	−0.016	−0.095	−0.069
	(0.073)	(0.072)	(0.029)	(0.026)	(0.033)	(0.030)	(0.054)	(0.052)
$\sum \gamma_\tau$	−0.004		0.053*		0.051*		0.065	
	(0.034)		(0.030)		(0.032)		(0.041)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	1,168,863	1,168,863	109,170	109,170	52,418	52,418	10,661	10,661
No. of banks	18,467	18,467	1,843	1,843	917	917	184	184
R^2	0.125	0.126	0.026	0.039	0.026	0.045	0.020	0.064

Table V

Maturity Transformation and Expense Betas

This table estimates the relationship between expense beta and repricing maturity. The data are quarterly and cover all U.S. commercial banks with at least 60 observations from 1997 to 2017. The repricing maturity of assets is estimated by calculating the weighted average repricing maturity of loans and securities (these data start in 1997) and assigning zero repricing maturity to cash and Fed funds sold. We average the repricing maturities across quarters. The interest expense betas are estimated according to equation (9) in the main text and winsorized at the 5% level. The control variables are the average wholesale funding ratio (sum of large time deposits, Fed funds purchased, and repos, divided by assets), the equity ratio (equity divided by assets), and the natural logarithm of average assets. Top 5% of banks (Panel B) are the largest 5% by average inflationadjusted assets over the sample. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

Panel A: All banks

	Repricing maturity				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−4.508***	−4.788***	−4.946***	−6.060***	−6.520***
	(0.514)	(0.554)	(0.544)	(0.592)	(0.644)
Wholesale funding ratio		0.872**			0.550*
		(0.173)			(0.202)
Equity ratio			−4.568***		−3.669***
			(0.259)		(0.277)
Log avg. assets				0.283***	0.270***
				(0.014)	(0.014)
Constant	5.203***	5.162***	5.842***	4.292***	4.819***
	(0.166)	(0.160)	(0.192)	(0.164)	(0.183)
No. of banks	5,328	5,328	5,328	5,328	5,328
R^2	0.047	0.048	0.058	0.094	0.101

Panel B: Top 5% of banks

	Repricing maturity				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−6.465***	−6.667***	−6.959***	−6.400***	−7.389***
	(1.186)	(1.223)	(1.210)	(1.193)	(1.275)
Wholesale funding ratio		0.635			1.224
		(0.370)			(0.414)
Equity ratio			−12.550***		−12.933***
			(0.978)		(1.072)
Log avg. assets				−0.027	0.011
				(0.022)	(0.024)
Constant	6.374***	6.343***	7.870***	6.579***	7.774***
	(0.445)	(0.434)	(0.508)	(0.466)	(0.509)
No. of banks	266	266	266	266	266
R^2	0.081	0.082	0.137	0.082	0.140

Table VI

Securities Share and Expense Betas

This table estimates the relationship between expense beta and the securities share of assets (the relationship between expense beta and the loan share has the same magnitude and opposite sign). The data are quarterly and cover all U.S. commercial banks with at least 60 observations from 1984 to 2017. The interest expense betas are calculated according to equation (9) in the main text and winsorized at the 5% level. The control variables are wholesale funding ratio (sum of large time deposits, Fed funds purchased, and repos, divided by assets), equity ratio (equity divided by assets), and the natural logarithm of average assets. Top 5% of banks (Panel B) are the largest 5% by average inflationadjusted assets over the sample. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

Panel A: All banks

	Securities/Assets				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−0.322***	−0.227***	−0.270***	−0.240***	−0.127***
	(0.043)	(0.043)	(0.044)	(0.040)	(0.041)
Wholesale funding ratio		−0.284***			−0.253***
		(0.037)			(0.030)
Equity ratio			0.642***		0.631***
			(0.028)		(0.025)
Log avg assets				−0.015***	−0.011***
				(0.001)	(0.001)
Constant	0.386***	0.390***	0.303***	0.428***	0.339***
	(0.016)	(0.012)	(0.018)	(0.011)	(0.011)
No. of banks	8,086	8,086	8,086	8,086	8,086
R^2	0.043	0.063	0.071	0.067	0.107

Panel B: Top 5% of banks

	Securities/Assets				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−0.243***	−0.254***	−0.258***	−0.206***	−0.239***
	(0.040)	(0.044)	(0.042)	(0.040)	(0.046)
Wholesale funding ratio		0.035			0.061
		(0.023)			(0.022)
Equity ratio			−0.490***		−0.519***
			(0.053)		(0.058)
Log avg assets				−0.013***	−0.014***
				(0.001)	(0.001)
Constant	0.323***	0.321***	0.376***	0.413***	0.472***
	(0.019)	(0.018)	(0.022)	(0.017)	(0.021)
No. of banks	404	404	404	404	404
R^2	0.031	0.032	0.063	0.054	0.090

Table VII

Sensitivity Matching within the Securities Portfolio

This table provides estimates of the matching of the sensitivities of interest expense and interest income from securities. The data are quarterly and cover all U.S. commercial banks with at least 60 observations from 2001 to 2017. The security and expense betas are estimated according to equation (9) in the main text and winsorized at the 5% level. We estimate the OLS regression

$$\beta_i^{Sec} = \alpha + \gamma \beta_i^{Exp} + \epsilon_i,$$

where β_i^{Sec} and β_i^{Exp} are bank i's security and expense beta, respectively. The security beta is estimated from interest income from total securities (columns (1) and (2)), Treasuries and agency debt (columns (3) and (4)), mortgage-backed securities (MBS, columns (5) and (6)), and other securities (columns (7) and (8)). Time FE denotes whether time fixed effects are included in the estimation of security and expense betas. Top 5% of banks (Panel B) are the largest 5% by average inflationadjusted assets over the sample. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

Panel A: All banks

	Total securities		Treasuries & agency debt		MBS		Other securities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Int. exp. beta	0.266***	0.259***	0.377***	0.365***	0.258***	0.240***	0.241***	0.239***
	(0.035)	(0.034)	(0.066)	(0.065)	(0.088)	(0.088)	(0.064)	(0.063)
Constant	0.099***	0.096***	0.131***	0.127***	0.098***	0.099***	−0.027**	−0.026**
	(0.033)	(0.035)	(0.037)	(0.040)	(0.065)	(0.062)	(0.025)	(0.023)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of banks	4,108	4,108	2,979	2,979	2,383	2,383	3,258	3,258
R^2	0.024	0.023	0.022	0.021	0.010	0.008	0.012	0.012

Panel B: Top 5% of banks

	Total securities		Treasuries & agency debt		MBS		Other securities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Int. exp. beta	0.589***	0.562***	0.793***	0.775***	0.473**	0.458**	0.564***	0.560***
	(0.134)	(0.119)	(0.204)	(0.212)	(0.251)	(0.239)	(0.282)	(0.284)
Constant	0.011	0.020	0.054	0.057	0.018	0.021	−0.070	−0.064
	(0.064)	(0.060)	(0.080)	(0.081)	(0.111)	(0.103)	(0.103)	(0.101)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of banks	205	205	148	148	119	119	162	162
R^2	0.102	0.094	0.077	0.074	0.043	0.041	0.051	0.049

Table VIII

Market Power and Interest Sensitivity Matching

This table estimates the effect of market power on interest rate sensitivity matching. The data are quarterly and cover all U.S. commercial banks with at least 60 observations from 1994 to 2017. The results are from the two-stage OLS regression

$$\begin{aligned} \beta_i^{Exp} &= \alpha + \gamma HHI_i + \epsilon_i, \quad \text{[Stage 1]} \\ \beta_i^{Inc} &= \alpha + \delta \widehat{\beta_i^{Exp}} + \epsilon_i, \quad \text{[Stage 2]} \end{aligned}$$

where HHI_i is bank i's market concentration, β_i^{Inc} and β_i^{Exp} are estimated according to equation (9) in the main text, and $\widehat{\beta_i^{Exp}}$ is the predicted interest expense beta from the first stage. To calculate market concentration, we construct a Herfindahl-Hirschman index (HHI) of branch share at the county level, and then average them across each bank's branches, using the number of branches as weights. Columns (1) and (2) present the results in the first stage while columns (3) and (4) present results in the second stage. Time FE denotes whether time fixed effects are included in the estimation of income and expense betas. Income and expense betas and HHIs are winsorized at the 5% level. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

	First stage		Second stage	
	(1)	(2)	(3)	(4)
HHI score	−0.092***	−0.094***		
	(0.022)	(0.021)		
$\widehat{IntExpBeta}$			0.917***	0.953***
			(0.347)	(0.351)
Constant	0.340***	0.338***	0.048	0.036
	(0.025)	(0.026)	(0.120)	(0.120)
Time FE	No	Yes	No	Yes
No. of banks	5,720	5,720	5,720	5,720
R^2	0.013	0.014	0.208	0.202

Table IX

Retail Deposit Betas and Interest Sensitivity Matching

This table examines the effect of retail deposit betas on interest rate sensitivity matching. The data are quarterly and cover all U.S. commercial banks with at least 60 observations from 1997 to 2017. The results are from the following two-stage OLS regression

$$\beta_i^{Exp} = \alpha + \gamma RetailBeta_i + \epsilon_i, \quad \text{[Stage 1]}$$
$$\beta_i^{Inc} = \alpha + \delta \widehat{\beta_i^{Exp}} + \epsilon_i, \quad \text{[Stage 2]}$$

where $RetailBeta_i$ is bank i's retail beta, β_i^{Inc} and β_i^{Exp} are estimated according to equation (9) in the main text and winsorized at the 5% level, and $\widehat{\beta_i^{Exp}}$ is the predicted interest expense beta from the first stage. Retail deposit betas are calculated at the county level using Ratewatch data for interest checking, $25k money market accounts, and $10k 12-month CDs, and then averaged across branches for each bank-product (using branch deposits as weights) and across products for each bank. Columns (1) to (4) estimate retail betas without controlling for bank-time fixed effects. Columns (5) to (8) estimate retail betas controlling for bank-time effects. Time FE denotes whether time fixed effects are included in the estimation of income and expense betas. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

	Across-bank				Within-bank			
	First stage		Second stage		First stage		Second stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retail beta	0.510***	0.514***			0.145***	0.146***		
	(0.050)	(0.049)			(0.018)	(0.018)		
$Int\widehat{ExpB}eta$			0.939***	0.943***			0.834***	0.841***
			(0.139)	(0.140)			(0.375)	(0.372)
Constant	0.315***	0.307***	0.033	0.031	0.320***	0.312***	0.066	0.063
	(0.027)	(0.030)	(0.043)	(0.042)	(0.028)	(0.032)	(0.129)	(0.125)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of banks	4,714	4,714	4,714	4,714	4,390	4,390	4,390	4,390
R^2	0.065	0.066	0.182	0.180	0.008	0.008	0.214	0.211

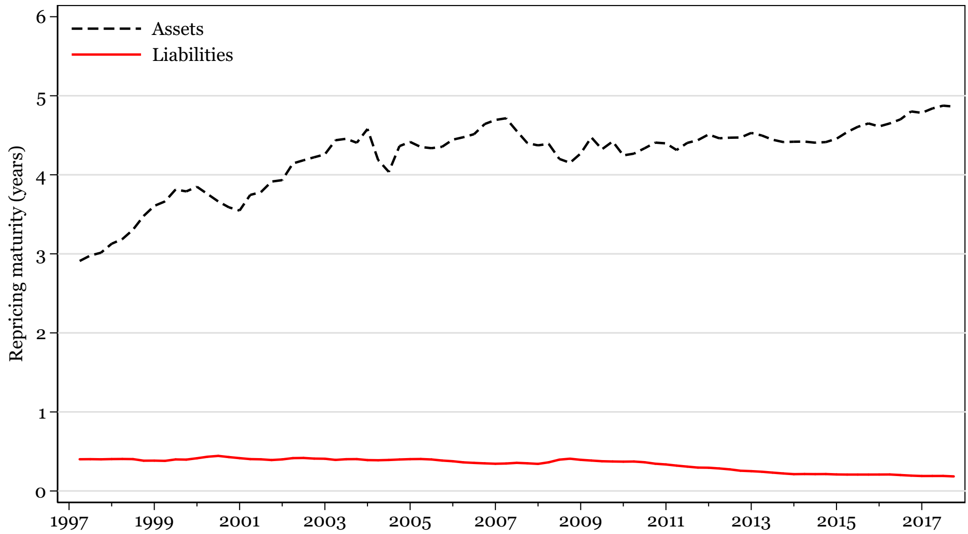

Figure 1. **Repricing maturity of aggregate bank assets and liabilities**. The figure plots the repricing maturity, a rough proxy for duration, of the assets and liabilities of the aggregate banking sector. The repricing maturity of assets is estimated by calculating the repricing maturity of loans and securities using the available data and assigning zero repricing maturity to cash and Fed funds sold. The repricing maturity of liabilities is calculated by assigning zero repricing maturity to transaction deposits, savings deposits, and Fed funds purchased, by assigning repricing maturity of five to subordinated debt, and by calculating the repricing maturity of time deposits using the available data. All other asset and liabilities categories (e.g., trading assets, other borrowed money), for which repricing maturity is not given, are left out of the calculation. The sample period is 1997 (when repricing maturity data become available) to 2017.

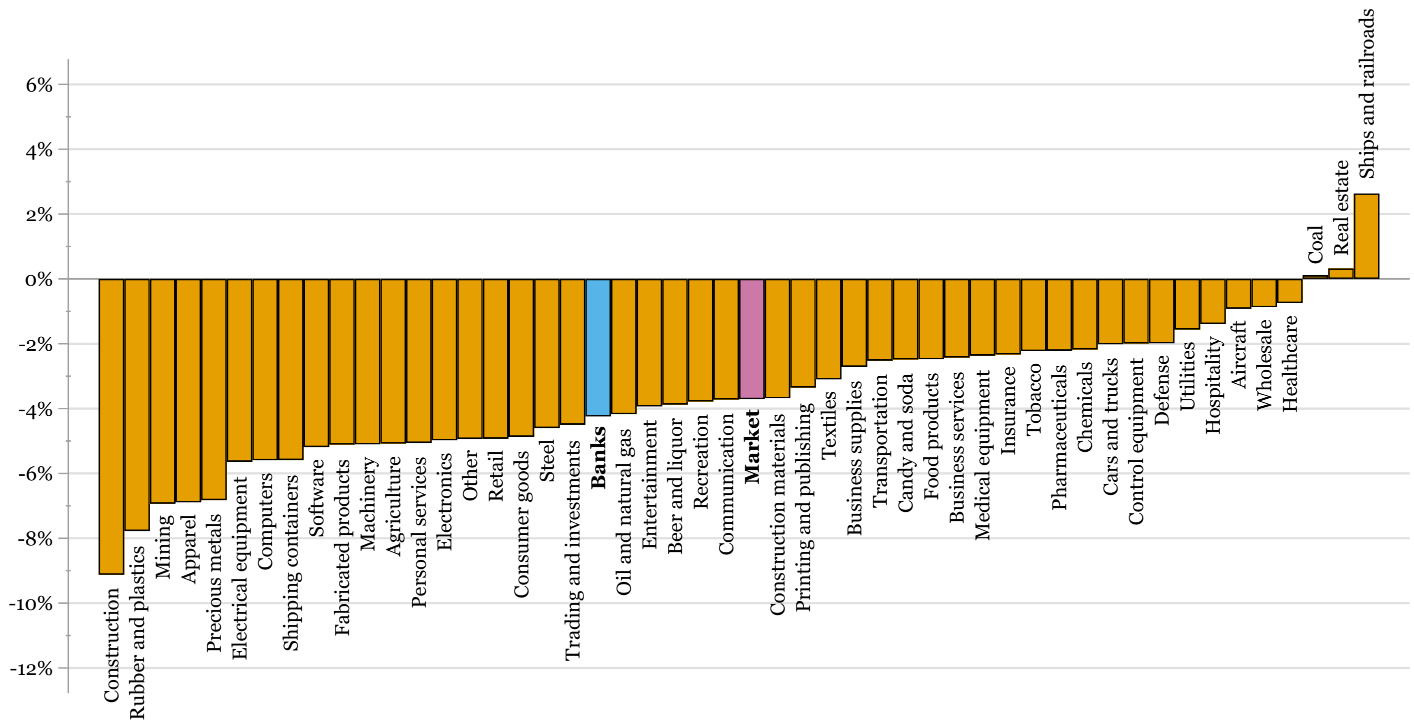

Figure 2. **Industry-level stock returns and interest rate changes**. The figure shows the sensitivity of bank and other industry stock portfolios to FOMC rate changes. The data are the returns of the Fama-French 49 industry portfolios and the CRSP value-weighted market portfolio, downloaded from Ken French's website. The figure plots the coefficients from regressions of these industry returns on the change in the one-year Treasury rate (obtained from the Fed's H.15 release) over a one-day window around FOMC meetings. The sample includes all scheduled FOMC meetings from January 1994 to June 2007 (there are 108 such meetings and five unscheduled ones).

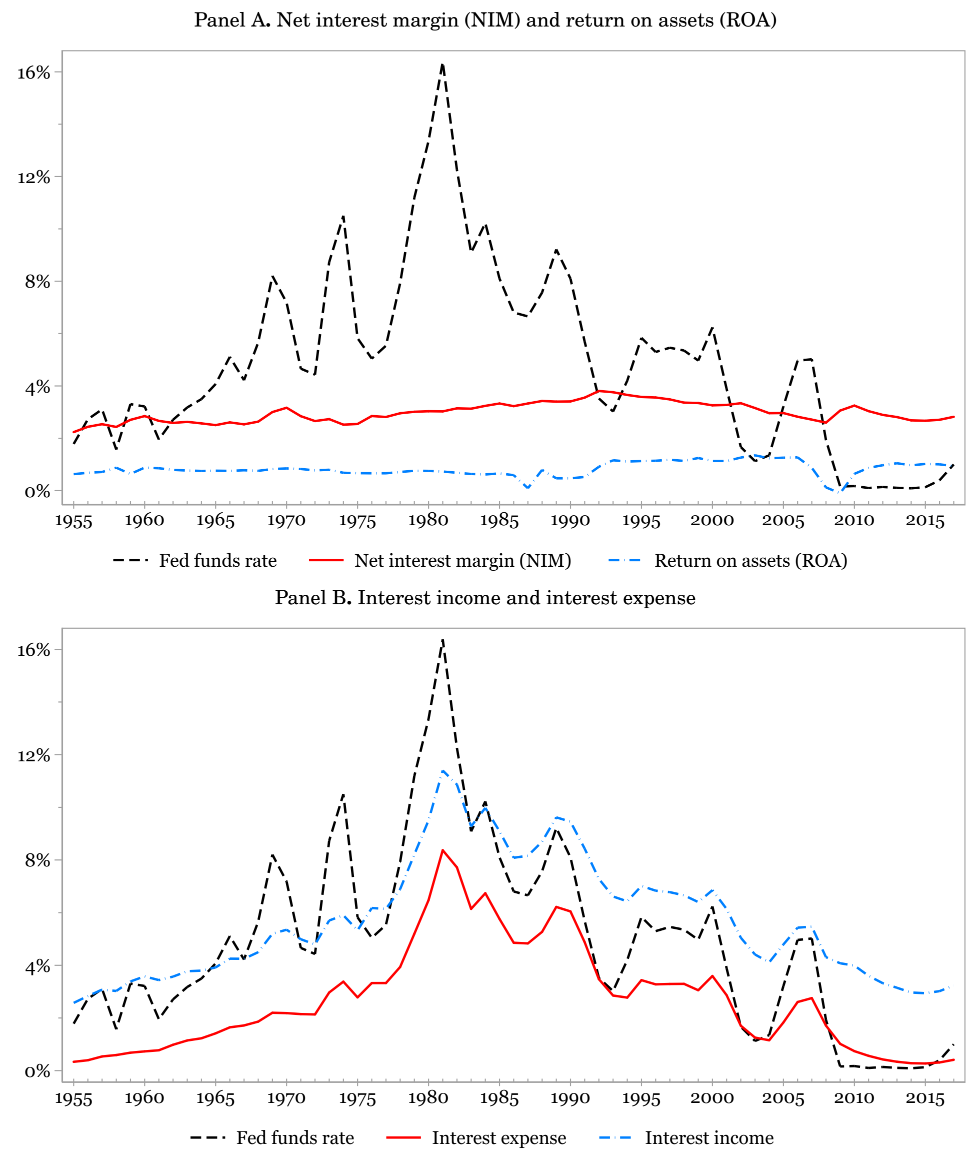

Figure 3. **Aggregate time series**. The figure plots the aggregate time series of net interest margin (NIM) and return on assets (ROA) in Panel A, and the interest income and interest expense rates in Panel B. Also shown is the Fed funds rate. The interest income and expense rates equal total interest income and expense divided by assets, respectively. The data are annual from the FDIC, 1955 to 2017.

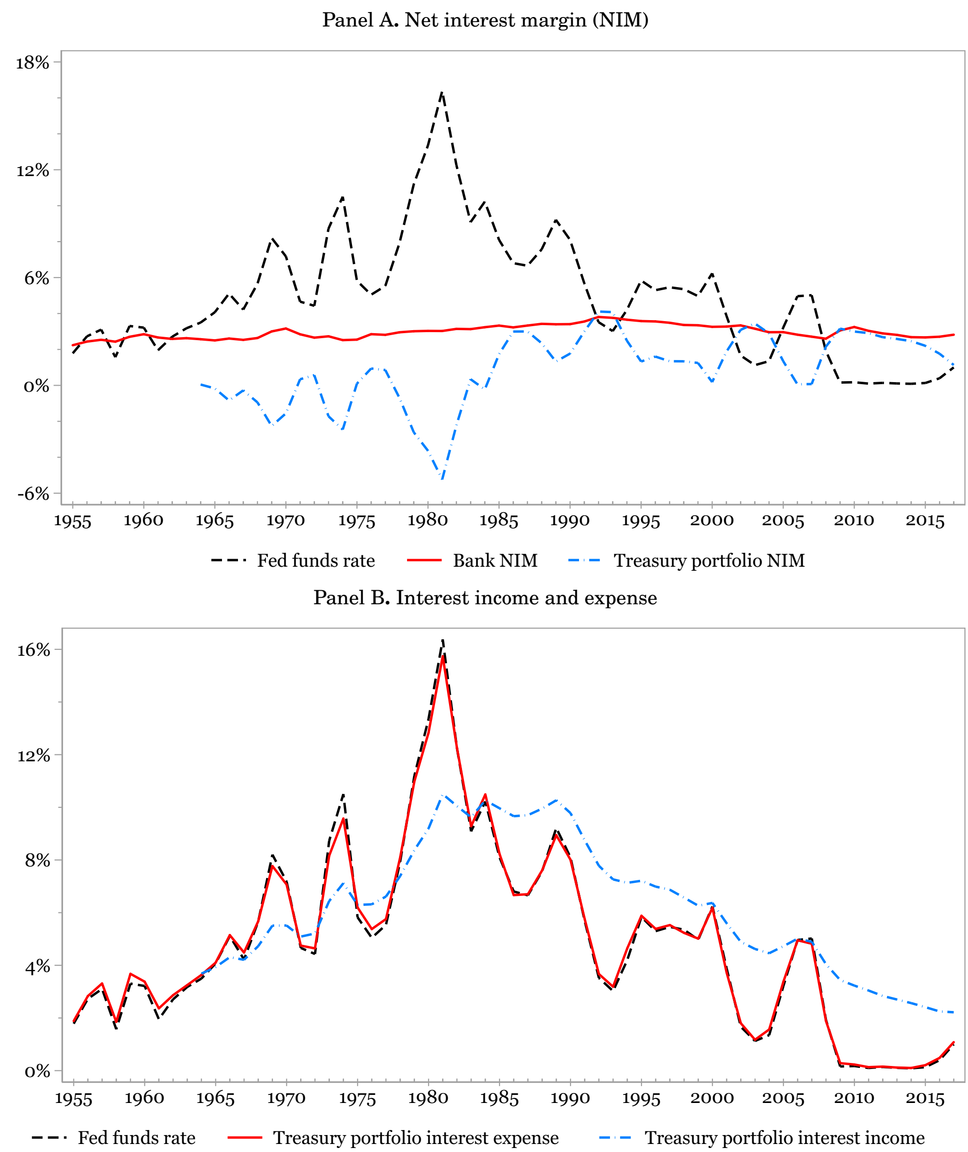

Figure 4. **Simulated Treasury portfolio net interest margin (NIM)**. The figure plots the NIM (Panel A) and interest income and interest expense (Panel B) of a mimicking portfolio of Treasury bonds constructed to have the same duration mismatch as banks. The Treasury mimicking portfolio is constructed to replicate banks' interest income as in Section IV of the Internet Appendix. It invests 26.7% at the Fed funds rate and 73.3% in a buy-and-hold portfolio of ten-year Treasury bonds, giving it an implied duration of 3.7 years. The Treasury mimicking portfolio is funded by borrowing 34% at the one-year Treasury rate and 66% at the Fed funds rate for a target liabilities duration of 0.34 years. The portfolio's NIM interest income, and interest expense are computed using standard book accounting. The data are annual from the Federal Reserve, 1955 to 2017.

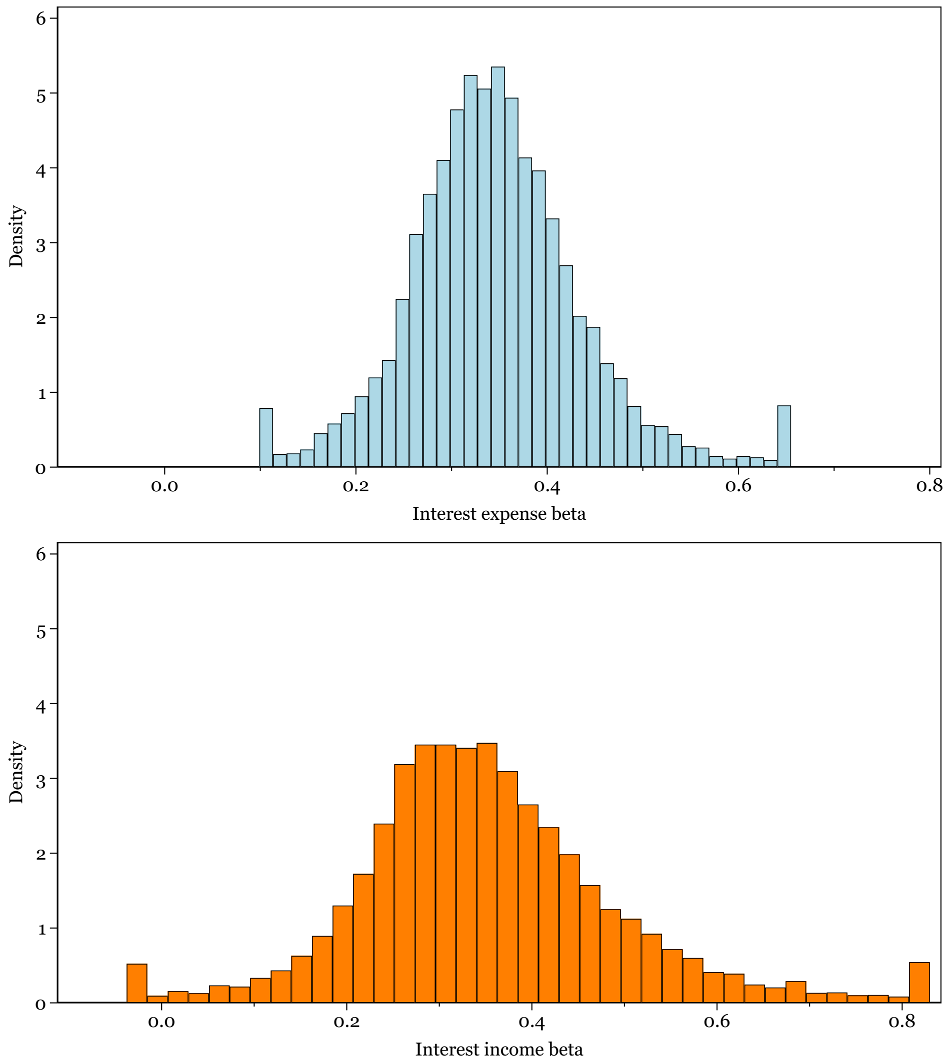

Figure 5. **The distributions of interest expense and income betas**. The interest expense and income betas are calculated by regressing the change in a bank's interest expense or income rate on the contemporaneous and previous three quarterly changes in the Fed funds rate. The sample includes all banks with at least 60 quarterly observations from 1984 to 2017. For this figure, the betas are winsorized at the 1% level.

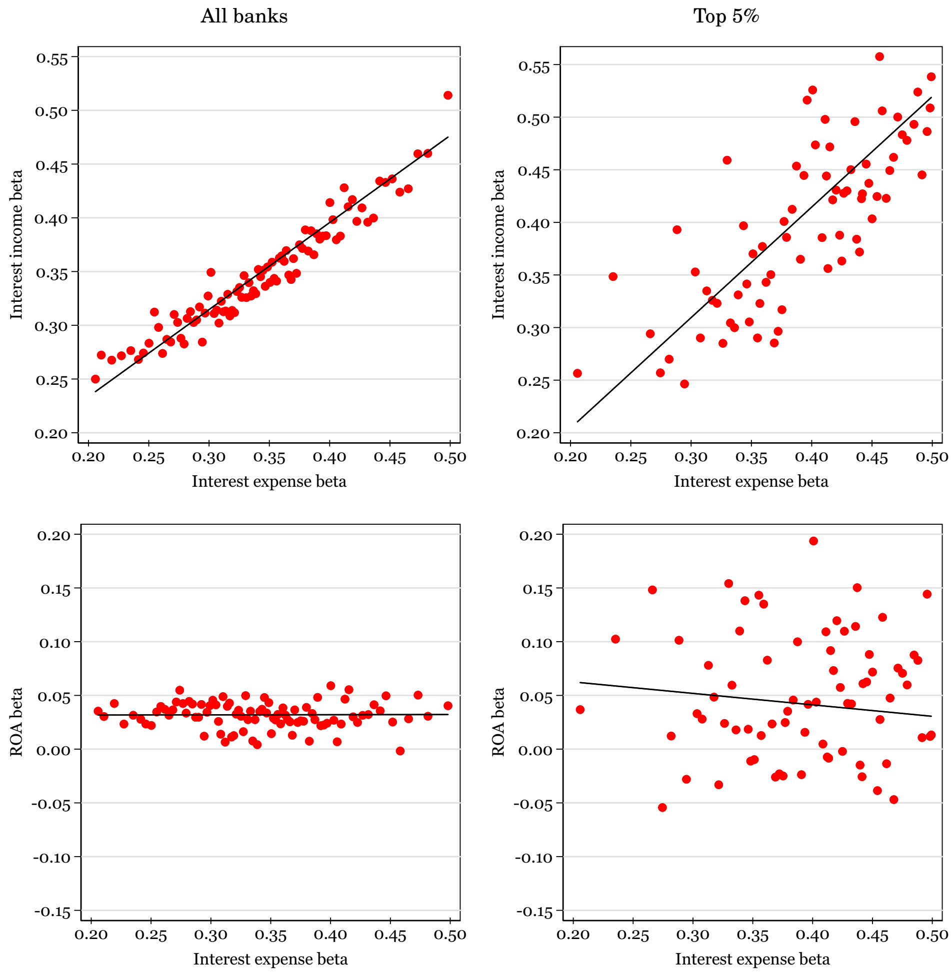

Figure 6. **Interest expense, interest income, and return on assets (ROA) matching**. This figure shows binned scatter plots of interest expense, interest income, and ROA betas for all banks and the largest 5% of banks. The betas are calculated by regressing the quarterly change in each bank's interest expense rate, interest income rate, or ROA on the contemporaneous and previous three changes in the Fed funds rate. Only banks with at least 60 quarterly observations are included. The betas are winsorized at the 5% level. The binned scatter plot groups banks into 100 bins by interest expense beta and plots the average income or ROA beta within each bin. The top 5% of banks are those whose average total assets over the sample are in the top fifth percentile. The sample period is 1984 to 2017.

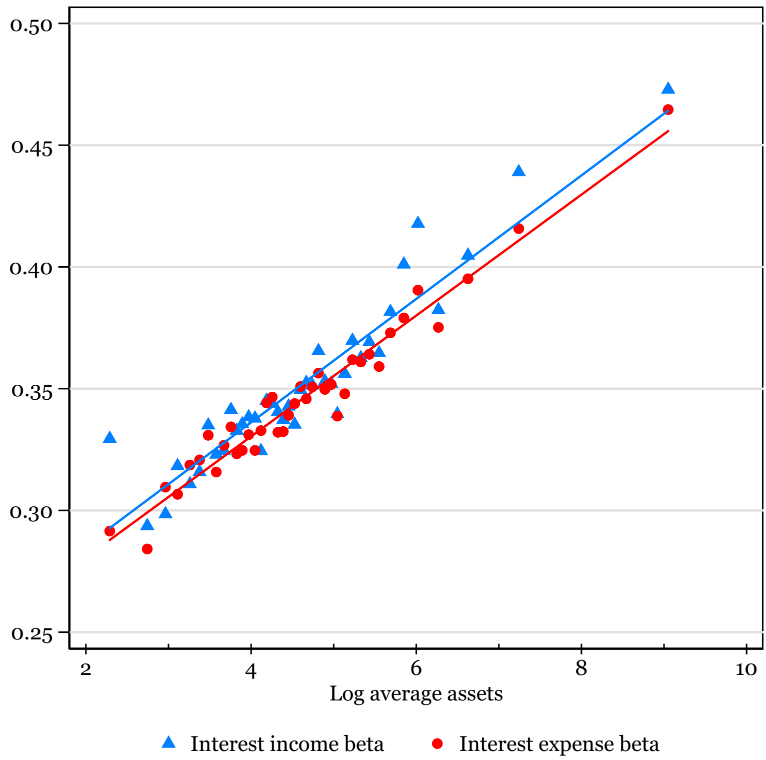

Figure 7. **Interest expense and interest income betas by asset size**. This figure shows a binned scatter plot of interest expense betas and interest income betas against the log of average assets. The betas are calculated by regressing the quarterly change in each bank's interest expense rate or interest income rate on the contemporaneous and previous three changes in the Fed funds rate. The betas are not winsorized. The sample are banks with at least 60 quarterly observations from 1984 to 2017 (8,086 banks). The binned scatter plot groups banks into 40 bins by log assets and plots the average income or expense beta within each bin.

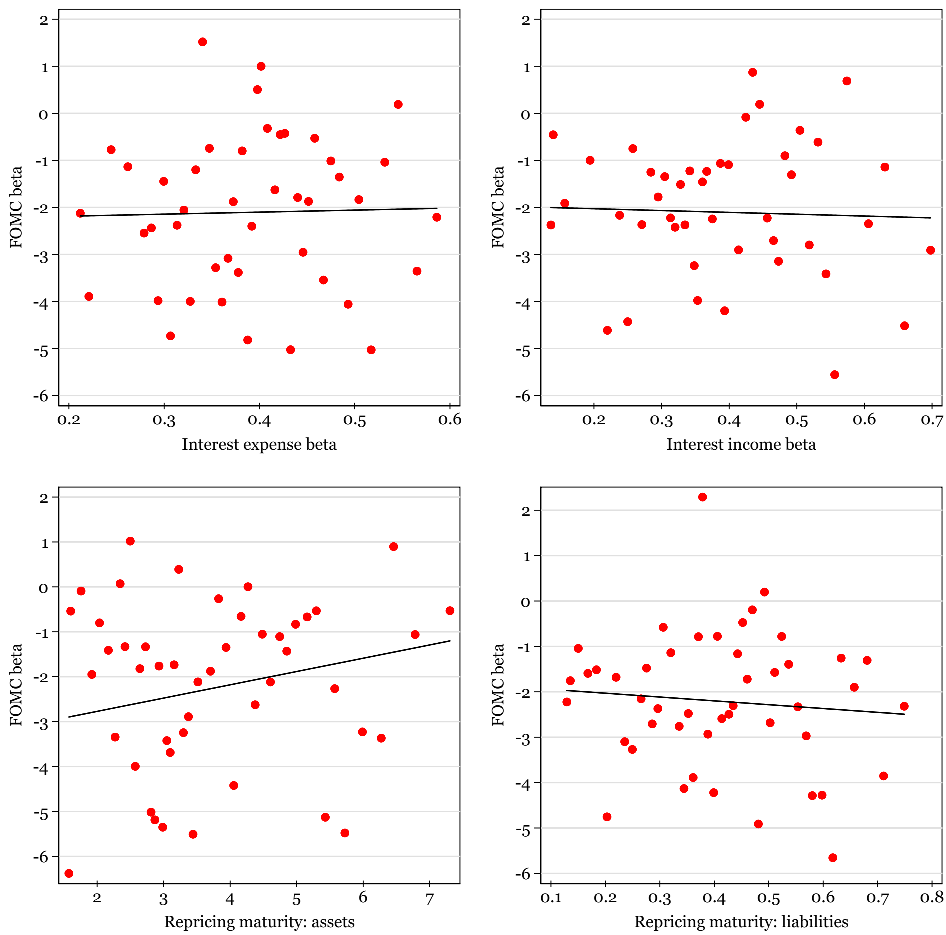

Figure 8. **Equity FOMC betas**. This figure shows binned scatter plots of banks' equity FOMC betas against their interest expense betas (top left), interest income betas (top right), asset repricing maturity (bottom left), and liabilities repricing maturity (bottom right). The FOMC betas are calculated by regressing the stock return of publicly listed banks on the change in the one-year Treasury rate over a one-day window around scheduled FOMC meetings. Expense and income betas are calculated by regressing the quarterly change in each bank's interest expense or income on the contemporaneous and previous three changes in the Fed funds rate. The sample includes all publicly listed banks with at least 20 quarterly observations. The betas are winsorized at the 5% level. The binned scatter plot groups the bank holding companies into 50 bins and plots the average FOMC beta within each bin. The sample period is January 1994 to June 2007.

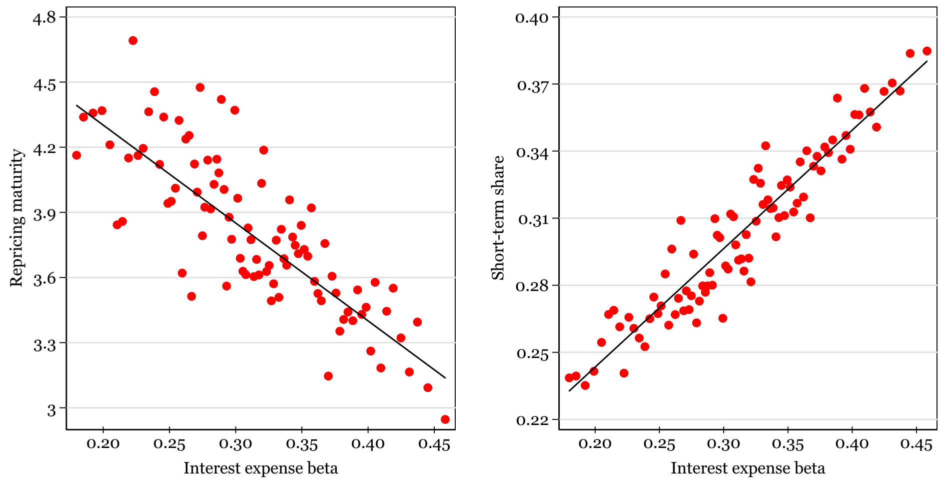

Figure 9. **Interest expense betas and proxies for asset duration**. This figure shows binned scatter plots of the repricing maturity and short-term share of loans and securities against interest expense betas. Repricing maturity is calculated as a weighted average of the amounts reported within each interval (e.g., loans with repricing maturity of one to three years are assigned a repricing maturity of two years). The short-term share refers to loans and securities with repricing maturity of less than one year as a percentage of the total. The betas are calculated by regressing the quarterly change in each bank's interest expense rate on the contemporaneous and previous three changes in the Fed funds rate. Only banks with at least 60 quarterly observations are included and the betas are winsorized at the 5% level. The binned scatter plot groups banks into 100 bins by interest expense beta and plots the average repricing maturity and short-term share within each bin. The sample period is 1997 to 2017.

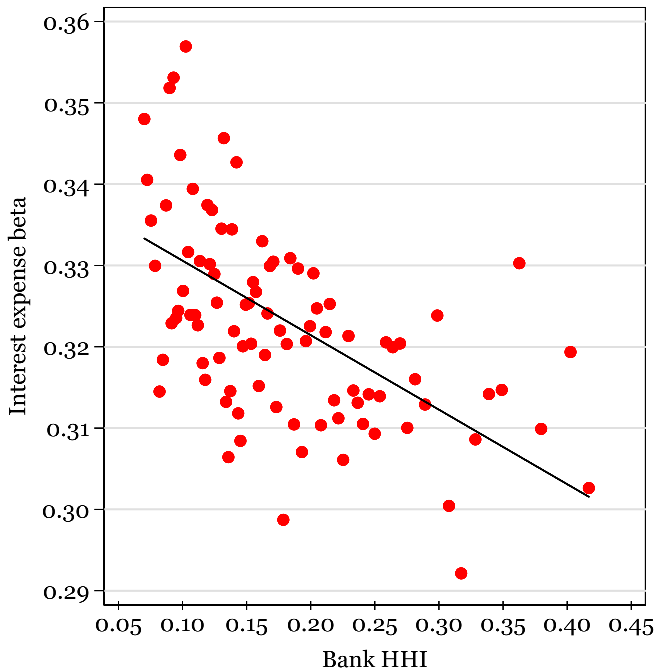

Figure 10. **Interest expense betas and market concentration**. This figure presents a binned scatter plot of interest expense betas against a bank Herfindahl-Hirschman index (HHI). To calculate the bank HHI, we first calculate a county HHI by computing each bank's share of the total branches in the county and summing the squared shares. We then create the bank HHI by averaging the county HHIs of each bank's branches, using the bank's number of branches in each county as weights. The HHIs are winsorized at the 5% level. The betas are calculated by regressing the change in a bank's interest expense rate on the contemporaneous and previous three quarterly changes in the Fed funds rate. Only banks with at least 60 quarterly observations are included. The betas are winsorized at the 5% level. The sample period is 1994 to 2017.