Banking on Deposits: Maturity Transformation without Interest Rate Risk

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Abstract

We show that in stark contrast to conventional wisdom maturity transformation does not expose banks to significant interest rate risk. Aggregate net interest margins have been near-constant from 1955 to 2015, despite substantial maturity mismatch and wide variation in interest rates. We argue that this is due to banks' market power in deposit markets. Market power allows banks to pay deposit rates that are low and relatively insensitive to interest rate changes, but it also requires them to pay large operating costs. This makes deposits resemble fixed-rate liabilities. Banks hedge them by investing in long-term assets whose interest payments are also relatively insensitive to interest rate changes. Consistent with this view, we find that banks match the interest rate sensitivities of their expenses and income one for one. This relationship is robust to instrumenting for expense sensitivity using geographic variation in market power. Also consistent, we find that banks with lower expense sensitivity hold assets with substantially longer duration. Our results provide a novel explanation for the coexistence of deposit-taking and maturity transformation.

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I Introduction

A defining function of banks is maturity transformation—borrowing short term and lending long term. In textbook models, maturity transformation allows banks to earn the average difference between long- and short-term rates—the term premium—but it also exposes them to interest rate risk. An unexpected rise in the short-term rate drives up interest expenses relative to interest income, sinking net interest margins and depleting bank capital. Interest rate risk is therefore viewed as fundamental to the business of banking, and it underlies the discussion of how monetary policy impacts the health of the banking system.[1]

Banks do in fact engage in significant maturity transformation. From 1997 to 2013, the estimated average duration of aggregate bank assets is 4.3 years versus only 0.4 years for liabilities. The mismatch of roughly 4 years is large and stable. It implies that a 100-bps level shock to interest rates would lead to a 100-bps increase in expenses relative to income for 4 years, and hence a 4 percentage point cumulative reduction in net interest margins. This represents a big hit to profits for an industry with a 1% return on assets. In present value terms the shock would induce a 4% decline in assets relative to liabilities, and since banks are levered ten to one, a 40% decline in bank equity. The shock need not happen all at once; it can accumulate over time, and is small by historical standards.

Yet, in practice we find that a 100-bps shock to interest rates induces only a 2.4% decline in bank equity. This is shown in Figure 1, which plots the coefficients from regressions of industry portfolio returns on changes in the one-year Treasury rate around Federal Open Market Committee (FOMC) meetings.[2] In addition to being relatively small, the coefficient for banks (-2.42) is also very similar to that for the overall market portfolio (-2.26) and is close to the median among the 49 industries. Thus, banks are no more exposed to interest rate shocks than the typical nonfinancial firm.

[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).

[2]We use the value-weighted Fama-French 49 industry portfolios, available on Ken French's website. We use a two-day-window around FOMC meetings as in Hanson and Stein (2015). The sample is from 1994 (when the FOMC began making announcements) to 2008 (when the zero lower bound was reached). We focus on the 113 scheduled meetings over this period (the 5 unscheduled ones are contaminated by other types of interventions). The results are unaffected if we use other maturities, or if we identify a level shift in the yield curve by controlling for slope changes.

To understand this low exposure, we analyze bank cash flows. We show that, in stark contrast to the textbook view, they are insensitive to interest rate changes. Panel A of Figure 2 plots banks' aggregate net interest margin (NIM), which is the difference between interest income and expenses as a percentage of assets. NIM is a standard measure of bank profitability that captures the impact of interest rates on bank cash flows. From 1955 to 2015, aggregate NIM stayed in a narrow band between 2.2% and 3.7% even as the short-term interest rate (the Fed funds rate) fluctuated between 0% and 16%. Moreover, movements in NIM within this band have been very slow and gradual: yearly NIM changes have a standard deviation of just 0.13% and zero correlation with the Fed funds rate. This lack of sensitivity flows through to banks' bottom line: return on assets (ROA) displays virtually no relationship with interest rate fluctuations.

We show that bank cash flows have no exposure to interest rates because banks closely match the interest rate sensitivity of their income and expenses. This is shown at the aggregate level in Panel B of Figure 2. Interest income has a low sensitivity to the short rate. This is expected since banks' assets are primarily fixed-rate and long-term. What is surprising is that banks are able to match this low sensitivity on the expense side despite having liabilities that are overwhelmingly of zero or near-zero maturity. This is due to banks' market power in retail deposit markets (Drechsler, Savov, and Schnabl 2017), which allows them to keep deposit rates low even as market rates rise. Since retail (core) deposits are over 70% of bank liabilities, the overall sensitivity of banks' interest expenses is low. Market power thus allows banks to simultaneously maintain a large maturity mismatch and yet a near-perfect match in the interest sensitivities of their income and expenses, i.e. to engage in maturity transformation without interest rate risk.[3]

In fact, banks not only can but *must* engage in maturity transformation in order to avoid interest rate risk. Since their expenses are insensitive, holding only short-term assets would expose banks to the risk of a decline in interest rates. Such a decline would cause interest income to fall relative to expenses, making banks unable to cover the large operating costs (salaries, branches, marketing) associated with running a deposit franchise and obtaining

[3]Under the textbook view, a level shift in interest rates would cause a fourfold cumulative change in NIM. Figure A.1 in the appendix shows what this would look like using data from 1955 to 2015. We thank Adi Sunderam for the suggestion.

market power. These costs are reflected (net of fee income) in the sizable 2% to 3% gap between NIM and ROA in Panel A of Figure 2. To hedge these costs against a drop in interest rates, banks must hold sufficient long-term fixed-rate assets.

These facts add up to a simple view of banks' business model. It is built on a foundation of core deposits, which give banks stable and predictable expenses and allow them to invest in long-term assets.[4] This generates a NIM of about 3%, out of which banks pay 2% in net operating costs to maintain their deposit base. This leaves a 1% ROA, which banks lever up ten to one into a 10% return on equity (ROE). Market power in deposit markets keeps these numbers steady year in and year out, making this business model viable.

We present a simple model that captures this view. In the model, banks pay a fixed operating cost each period to maintain a deposit franchise. This gives them market power and allows them to pay a deposit rate that is only a fraction of the economy's short-term rate as in Drechsler, Savov, and Schnabl (2017). As a result, their expenses are relatively insensitive to interest rates. To hedge them, banks invest in assets with relatively insensitive income streams, i.e. long-term fixed-rate assets. Under free entry (zero ex ante deposit rents), banks exactly match the sensitivities of their interest income and expenses. The model thus explains the sensitivity matching of aggregate interest income and expenses and the stability of NIM and ROA in Figure 2. The model further implies that these results should hold bank by bank. We test this prediction in the cross section.

We do so using quarterly Call Report data on all U.S. commercial banks from 1984 to 2013.[5] We estimate each bank's interest expense sensitivity by regressing the change in its interest expense rate (interest expense divided by assets) on contemporaneous and lagged changes in the Fed funds rate. We then sum the coefficients to obtain a bank-level estimated sensitivity, which we call the interest expense beta. We compute an interest income beta for each bank analogously. The average expense beta (0.360) and average income beta (0.379) are very similar. They show that the rates banks pay and earn on average rise by just over a third of the rise in the Fed funds rate. At the same time, there is substantial variation in expense and income betas across banks in the 0.1 to 0.6 range.

[4] Hanson, Shleifer, Stein, and Vishny (2015) put forward a related view based on the stability of deposits with respect to liquidity (run) risk. We think of these as working in tandem.

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

We find that our expense and income beta estimates line up strongly across banks. The raw correlations are 51% among all banks and 58% among the largest 5% of banks. The corresponding slopes from a univariate regression of income betas on expense betas are 0.768 and 0.878. The high correlations and slope coefficients close to one show that there is strong matching, as predicted by the model. These results are confirmed in two-stage panel regressions with time fixed effects, which give estimates that are more precise and for large banks closer to one (0.765 for all banks, 1.114 for the top 5%). The strong matching leaves banks' profitability largely unexposed: ROA betas (computed in the same way as expense betas) are close to zero across the distribution of banks. Banks are thus able to engage in maturity transformation without exposing their bottom line to significant interest rate risk.

Our results predict that a bank with an expense beta of one would have an income beta close to one. While these betas are outside the range of our sample, they have predictive power out of sample. In particular, they accurately describe money market funds, which obtain funding at the Fed funds rate and hold only short-term assets, i.e. they do not engage in maturity transformation.

The insensitivity of banks' profits to interest rate shocks is confirmed when we look at the reactions of their stock prices. Following the methodology behind Figure 1, we construct "FOMC betas" for all publicly traded commercial banks. As in Figure 1, the average FOMC beta is similar to that of the overall market. Across banks, FOMC betas are flat in both expense and income betas. The latter result in particular shows that the share of long-term assets on a bank's balance sheet, as reflected in its income beta, is unrelated to the interest rate exposure of its stock price. This is explained by the high degree of sensitivity matching between assets and liabilities.

Our model predicts that banks with lower expense betas should have lower income betas and thus hold more long-term fixed-rate assets. We test this prediction using an estimate of asset duration available from the Call Reports after 1997. The estimate is repricing maturity, which is defined as the time until an asset's interest rate resets.[6] We find a strong negative relationship between estimated duration and interest expense betas. The regression

[6]Note that repricing maturity contrasts with remaining maturity, which is the time until the asset terminates. An example illustrating the important difference is a floating rate bond whose repricing maturity is one quarter even as its remaining maturity can be many years.

coefficient is -3.951 years, and is robust to a number of controls (wholesale funding, capitalization, size). The magnitude is similar to the average duration of bank assets and again extrapolates to fit the duration of money market funds.

We consider alternative explanations for our matching results. One possibility is that banks with higher expense betas face more run (liquidity) risk, which leads them to hold more short-term assets as a buffer. Although this explanation does not predict one-to-one matching, it goes qualitatively in the same direction. We address it by looking at the composition of banks' balance sheets, specifically at the shares of loans versus securities. Because loans are much less liquid than securities, the liquidity risk explanation predicts that high expense-beta banks hold fewer loans and more securities. We find the exact opposite: low expense-beta banks hold fewer loans and more securities. This finding fits our model because securities have substantially higher average duration (8.8 years versus 3.8 years for loans). Liquidity risk is thus unlikely to explain our results.[7]

We also consider the possibility that the sensitivity matching 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-to-one matching. Nevertheless, we test it by examining whether banks match the interest income betas of their securities holdings to their interest expense betas. Since securities are bought and sold in open markets, they are immune to market segmentation. We once again find close matching, even when we focus narrowly on banks' holdings of Treasuries and agency MBS. This shows that banks actively match their interest income and expense sensitivities.

Finally, we provide direct evidence for the market power mechanism underlying our model by exploiting three sources of geographic variation in market power. The first is local market concentration. We find that banks that raise deposits in more concentrated markets have lower expense betas and lower income betas, and that the coefficient for the matching relationship is again close to one. Thus banks match variation in expense betas that is due to market power, as predicted by our model.

[7]In addition to loans and securities, a small fraction of banks (about 8%) make use of interest rate derivatives. In principle, banks can use these derivatives to hedge the interest rate exposure of their assets, yet the literature has shown that they actually use them to increase it (Begenau, Piazzesi, and Schneider 2015). We show that our sensitivity matching results hold both for banks that do and do not use interest rate derivatives. Hence, derivatives use does not drive our results.

For the second source of variation we use branch-level data on retail deposit products (interest checking, savings, and small time deposits) from the data provider Ratewatch. These deposits are marketed directly to households in local markets and are thus 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 the average rates paid on these retail deposits in each county on Fed funds rate changes to obtain a county-level retail deposit beta. We then take a weighted average of these county betas to obtain a retail deposit beta for each bank, using the shares of the bank's branches in each county as weights. We show that banks' retail deposit betas are strongly related to their overall expense betas. Moreover, banks again match their income betas one for one to the differences in overall expense betas induced by variation in retail deposit betas.

For the third source of variation, we take this approach one step further and add bank-time fixed effects in the estimation of the county-level retail deposit betas. Thus, the resulting betas are identified only from differences in retail deposit rates across branches of the same bank. This purges the betas of any time-varying bank characteristics (e.g., loan demand), giving us a clean measure of local market power. Using the purged betas as an instrument for banks' overall expense betas, we once again find one-for-one matching between income and expense sensitivities.

The rest of this paper is organized as follows. Section II discusses the related literature; Section III presents the model; Section IV discusses the data; Section V presents our main results on matching; Section VI looks at the asset side of bank balance sheets; Section VII shows our results on market power; and Section VIII concludes.

II 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, Shleifer, Stein, and Vishny 2015). Central to this literature is the liquidity risk inherent in issuing runnable deposits.[8] Our paper focuses on the interest rate risk inherent in issuing deposits while engaging in maturity transformation. We argue that market power in deposit markets lowers the interest rate sensitivity of banks' expenses, making them resemble fixed-rate liabilities. As a consequence, banks hold long-term assets so that they face minimal net interest rate exposure. This explains how the banking sector has achieved stable profitability in the face of wide fluctuations in interest rates over the past sixty years.

An important distinction of our explanation for banks' maturity transformation is that it does not rely on the presence of a term premium. In Diamond and Dybvig (1983), a term premium is induced by household demand for short-term claims. In a recent class of dynamic general equilibrium models, maturity transformation varies with the magnitude of the term premium and banks' effective risk aversion (He and Krishnamurthy 2013, Brunnermeier and Sannikov 2014, 2016, Drechsler, Savov, and Schnabl 2015). In Di Tella and Kurlat (2017), as in our paper, deposit rates are relatively insensitive interest rate changes (due to capital constraints instead of 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.[9] In contrast, our paper focuses on risk *management* rather than risk *taking*. While both risk taking and risk management are consistent with some maturity transformation, only the risk-management explanation gives the strong quantitative prediction of one-to-one matching between between banks' interest income and expense sensitivities.[10]

Another important distinction is that our explanation implies that banks are relatively insulated from the balance sheet channel of monetary policy (Bernanke and Gertler 1995), which works through the influence of interest rate changes on bank net worth. It also addresses the concern that maturity transformation leads to financial instability (Kohn 2010).

[8]For measures of liquidity risk in the banking sector, see Brunnermeier, Gorton, and Krishnamurthy (2012) and Bai, Krishnamurthy, and Weymuller (2016).

[9]The Treasury 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 stable or actually increased.

[10]Consistent with the risk management view, Bank of America's (2016) annual report reads, "Our overall goal is to manage interest rate risk so that movements in interest rates do not significantly adversely affect earnings and capital." Accordingly, in 2016 each of the top four U.S. banks reported in their annual report that a parallel upward shift in interest rates would exert a modest *positive* influence on net interest income. For formal models of bank risk management, see Froot, Scharfstein, and Stein (1994) and Nagel and Purnanandam (2015).

The risk of instability is sometimes invoked as an argument for narrow banking (the idea that banks should hold only short-term safe assets, see Pennacchi 2012). Our analysis suggests that narrow banking could actually make banks more unstable.

The empirical literature looks at banks' exposure to interest rate risk. In a small sample of fifteen banks, Flannery (1981) finds that bank profits have a surprisingly low exposure and frames this as a puzzle. Flannery and James (1984a) and English, den Heuvel, and Zakrajsek (2012) examine the cross section of banks' stock price exposures, but without comparing banks to the broader market as we do in Figure 1.[11]

One possibility is that banks use derivatives to hedge their interest rate risk exposure (see, e.g. Freixas and Rochet 2008). Under this view they are not really engaging in maturity transformation but rather transferring it to the balance sheets of their derivatives counterparties. Yet as Purnanandam (2007), Begenau, Piazzesi, and Schneider (2015) and Rampini, Viswanathan, and Vuillemey (2016) show, derivatives use is limited and may actually amplify banks' maturity mismatch. This is consistent with our explanation where banks have a maturity mismatch but are nevertheless hedged against interest rates.

As Drechsler, Savov, and Schnabl (2017) show, banks with insensitive deposit rates experience greater deposit outflows when interest rate go up (this is consistent with their higher market power). This causes their balance sheets to contract even though NIM remains the same. Combined with the results in this paper, this can shed light on why banks with a bigger income gap (a measure of maturity mismatch) contract lending more following interest rate increases (Gomez, Landier, Sraer, and Thesmar 2016).

A canonical example of interest rate risk in the financial sector comes from the Savings and Loans (S&L) crisis of the 1980s. An unprecedented rise in interest rates inflicted significant losses on these institutions, which were subsequently compounded by risk shifting (White 1991). We draw two lessons from this episode. Remarkably, unlike the S&L sector, the commercial banking sector saw no decline in NIM during this period (see Figure 2). Moreover, as White (1991) points out, the rise in interest rates happened to occur right after deposit rates were deregulated, making it difficult for S&Ls to anticipate the effect of such a

[11]The exposures in English, den Heuvel, and Zakrajsek (2012) are somewhat larger than ours because their sample includes unscheduled FOMC meetings. Nevertheless, they remain much smaller than expected and only slightly larger than the exposure of the whole market (see Bernanke and Kuttner 2005, Table III).

large shock on their funding costs. Thus, when it comes to banks' interest rate risk exposure the S&L crisis is in some ways the exception that proves the rule.

The deposits literature has documented the low sensitivity of deposit rates to market rates, a key ingredient of 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) estimates the effective duration of deposits, finding it to be higher than their contractual maturity, consistent with a low interest rate sensitivity.[12] Nagel (2016) and Duffie and Krishnamurthy (2016) extend the low sensitivity finding to a wider set of bank instruments. Brunnermeier and Koby (2016) argue that deposit rates become fully insensitive when nominal rates turn negative, and that this impacts bank profitability and undermines the effectiveness of monetary policy.

The deposits 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 in turn allows them to provide more liquidity to their borrowers. Hanson, Shleifer, Stein, and Vishny (2015) argue that banks are better suited to holding fixed-rate assets than shadow banks because deposits are more stable than shadow bank funding. Berlin and Mester (1999) show that deposits allow banks to smooth out aggregate credit risk. Kirti (2017) finds that banks with more floating-rate liabilities extend more floating-rate loans to firms. Our paper focuses on banks' exposure to interest rate risk and provides an explanation for the co-existence of deposit-taking and maturity transformation.

III Model

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. Its problem is to invest in assets so as to maximize

[12] These papers focus on the contribution of deposit rents to bank valuations. A recent paper in this area is Egan, Lewellen, and Sunderam (2016), which finds that deposits are the main driver of bank value.

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 the bank does not issue any equity. Though it is straightforward to incorporate equity, the bank is able to avoid losses and therefore 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 deposit customers. Importantly, the deposit franchise gives the bank market power, which allows it to pay a deposit rate of only

$$\beta^{Exp} f_t, \tag{1}$$

where $0 < \beta^{Exp} < 1$ and f_t is the economy's short rate process (i.e. the Fed funds rate). Drechsler, Savov, and Schnabl (2017) construct a model that micro-founds this deposit rate as an industry equilibrium among banks with deposit market power. A bank with high market power has a low value of β^{Exp}, while a bank with low market power, such as one funded mostly by wholesale deposits, has a β^{Exp} close to one. Note that deposits are short term. While adding long-term liabilities to the model is straightforward, they would not change the mechanism and hence we leave them out. Moreover, as documented above, banks' liabilities are largely short term.

On the asset side, we assume that markets are complete and prices are determined by the stochastic discount factor m_t. Like all investors, banks use this stochastic discount factor when valuing profits.[13] Their problem is thus

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

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

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

where INC_t is the time and state contingent income stream generated by the bank's asset

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

portfolio. Note that we normalize the bank's problem to one dollar of deposits, which is without loss of generality since the problem 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's income must always exceed its interest expenses $\beta^{Exp} f_t$ and operating costs c.

The bank faces two solvency risks. The first is that its interest expenses rise with the short rate ($\beta^{Exp} > 0$), so it must ensure that its income stream is also sufficiently positively exposed to f_t. 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, i.e., 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, because this 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 so can its portfolio share of short-term assets.

The second solvency risk the bank faces is due to its operating costs c, which are insensitive to the short rate. As a consequence, the bank's income must be *insensitive* enough so that it can cover these operating costs in case 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 another way, when f_t is low the bank's deposit franchise generates only small interest savings, 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.

These conditions pin down the bank's portfolio when it makes no excess rents, as is the case under free ex ante entry into the banking industry. We obtain the following.

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

$$INC_t = \beta^{Exp} f_t + c. \tag{5}$$

Hence the bank matches the interest sensitivities of its income and expenses:

$$\textit{Income beta} \;\equiv\; \beta^{Inc} \;=\; \frac{\partial INC_t}{\partial f_t} \;=\; \beta^{Exp} \;\equiv\; \textit{Expense beta.} \tag{6}$$

When there are no excess rents, the present value of the interest savings generated by the deposit franchise is equal to the present value of its operating costs.[14] 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 expenses. We test this prediction in the following sections by analyzing the cross section of banks.

Finally, although we allow asset markets to be complete, it is actually simple for the bank to implement equation (5) using standard assets. It can do so by investing β^{Exp} share of its assets in short-term bonds, and the remainder in long-term fixed-rate bonds. We use this observation to provide additional empirical tests of our model.

IV Data

Bank data. Our bank data is from the U.S. Call Reports provided by Wharton Research Data Services. We use data from January 1984 to December 2013. 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 datasets.

In part of the analysis, we use repricing maturity as a proxy for duration. The repricing maturity of an asset is the time until its rate resets or the asset terminates, whichever comes sooner. For instance, the repricing maturity of a floating-rate bond is one quarter, while the repricing maturity of a fixed-rate bond is its terminal maturity.

To calculate the repricing maturity of bank assets and liabilities, we follow the methodology in English, den Heuvel, and Zakrajsek (2012). Starting in 1997, banks report their holdings of five asset categories (residential mortgage loans, all other loans, Treasuries and

[14]Formally, the condition is $(1-\beta^{Exp}) = c \times E_0\left[\sum_{t=0}^{\infty}\frac{m_t}{m_0}\right] = c \times P_{\text{consol}}$, where P_{consol} is the price of a 1 dollar consol bond. $(1-\beta^{Exp})$ is the present value of the interest savings generated by the deposit franchise, while $c \times P_{\text{consol}}$ is the present value of the perpetuity of operating costs c. Thus, under ex ante free entry a lower expense beta β^{Exp} implies a higher operating cost c.

agency debt, MBS secured by residential mortgages, and other MBS) broken down into six bins by repricing maturity interval (0 to 3 months, 3 to 12 months, 1 to 3 years, 3 to 5 years, 5 to 15 years, and over 15 years). To calculate the overall repricing maturity of a given asset category, we assign the interval midpoint to each bin (and 20 years to the last bin) and take a weighted average using the amounts in each bin as weights.[15] We compute the repricing maturity of a bank's assets as the weighted average of the repricing maturities of all of its asset categories, using their dollar amounts as weights. In some tests we include cash and Fed funds sold in the calculation, assigning them a repricing maturity of zero.

We follow a similar approach to calculate the repricing maturity of liabilities. Banks report the repricing maturity of their small and large time deposits by four intervals (0 to 3 months, 3 to 9 months, 1 to 3 years, and over 3 years). We assign the midpoint to each interval and 5 years to the last one. We assign zero repricing maturity to demandable deposits such as transaction and savings deposits. We also assign zero repricing maturity to wholesale funding such as repo and Fed funds purchased. We assume a repricing maturity of 5 years for subordinated debt. We compute the repricing maturity of liabilities as the weighted average of the repricing maturities of all of these categories.

Figure 3 plots the repricing maturity of the aggregate assets and liabilities of the banking sector. The average aggregate asset duration is 4.12 years, rising slightly through the late 1990s and then leveling off at 4.5 years since the mid-2000s. The average aggregate liabilities duration is 0.37 years, declining to about 0.25 years towards the end of the sample. The aggregate banking sector thus exhibits a duration mismatch of about 4 years.

Figure A.2 in the appendix plots the distribution of asset and liabilities repricing maturity across banks, showing that it exhibits substantial variation. Table A.1 provides summary statistics for repricing maturity by asset category. We note in particular that securities have a substantially higher repricing maturity (5.8 years on average, 8.8 years in the aggregate) than loans (3.1 years on average, 3.8 years in the aggregate).

Branch-level deposits. Our data on deposits at the branch level is from the Federal Deposit Insurance Corporation (FDIC). The data cover the universe of U.S. bank branches

[15] For the "other MBS" category, banks only report two bins: 0 to 3 years and over 3 years. We assign repricing maturities of 1.5 years and 5 years to these bins, respectively.

at an annual frequency from June 1994 to June 2014. 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 2013. 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.

V Income and expense sensitivity matching

Our model predicts that banks match the interest rate sensitivities of their income and expenses. Figure 2 shows that this prediction is borne out at the aggregate level, resulting in highly stable aggregate NIM and ROA. In this section, we analyze matching at the bank level and shed light on the mechanism by which it is achieved.

V.A Interest expense betas

We measure the interest rate sensitivity of banks' expenses by regressing the change in their interest expense rate on changes in the Fed funds rate. Specifically, we run the following time-series OLS regression for each bank i:

$$\Delta IntExp_{it} = \alpha_i + \sum_{\tau=0}^{3} \beta_{i,\tau}^{Exp} \Delta FedFunds_{t-\tau} + \varepsilon_{it}, \tag{7}$$

where $\Delta IntExp_{it}$ is the change in bank i's interest expenses rate from t to $t+1$ and $\Delta FedFunds_t$ is the change in the Fed funds rate from t to $t+1$. The interest expense rate is total quarterly interest expense (including 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 to capture the cumulative effect of Fed funds rate changes over a full year.[16] Our estimate of bank i's expense beta is the sum of the coefficients in (7), i.e. $\beta_i^{Exp} = \sum_{\tau=0}^{3} \beta_{i,\tau}^{Exp}$. To calculate an expense beta, we require a bank to have at least five years of data over our sample, 1984 to 2013. This yields 18,552 banks.

The top panel of Figure 4 plots a histogram of banks' interest expense betas and Table 1 provides summary statistics. The average expense beta is 0.360, which means that interest expenses rise by 36 bps for every 100 bps increase in the Fed funds rate. The estimate is similar but slightly larger for the largest 5% of banks by assets, whose average expense beta is 0.448. There is significant variation across banks, with a standard deviation of 0.096.[17]

Panel A of Table 1 presents a breakdown of banks' characteristics by whether their expense beta is below or above the median for the full sample of banks. The characteristics are averaged over time for each bank. The table shows that differences in banks' expense betas are not explained by the repricing maturity of their liabilities, which is similar across the two groups (0.462 versus 0.416 years).[18] This is because repricing maturity does not at all capture banks' ability to keep rates low and insensitive on short-term liabilities.

Nevertheless, expense betas do predict the duration of bank assets. Low-expense beta banks have higher repricing maturity than high expense beta banks (3.6 years versus 3.1 years). Moreover, income and expense betas match in each group, and ROA betas are close to zero in both groups. Panel B of Table 1 shows the same results when focusing on the top 5% of banks.

[16] 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. For both interest income and interest expense, the impulse responses take about a year to build up and then flattens out. Our results are robust to including more lags.

[17] 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 2013 is \$6.763 trillion, which implies an increase in annual revenues of $(1 - 0.448) \times \$6{,}763 = \$37$ billion from a 100 bps increase in the Fed funds rate. The revenue increase is permanent as long as the Fed funds rate remains at the higher level. It is large compared to the banking sector's average annual net income of \$59.5 billion over this period.

[18] It is reflected in the somewhat higher proportion of core deposits among low-expense beta banks.

V.B Cross-sectional analysis

We compute interest income betas as in (7), but with interest income as the dependent variable. Interest income includes all interest earned on loans, securities, and other assets. Our model predicts that income and expense betas should match one for one. This strong quantitative prediction is unique to our theory, giving us a powerful test.

Table 1 shows summary statistics for interest income betas and the bottom panel of Figure 4 plots their distribution. The average income beta is 0.379 with a standard deviation of 0.147. The estimate for the largest 5% of banks is 0.446. As Figure 4 shows, the distributions of expense and income betas are very similar with nearly identical means. Moreover, as Table 1 shows, income betas are significantly lower for low-expense beta banks than high-expense beta banks (0.320 versus 0.437). Overall, income and expense betas line up well, both among all banks and the largest 5%, giving an early indication of tight matching.

The top two panels of Figure 5 provide a graphical representation of the relationship between income and expense betas. Each panel shows a bin scatter plot which 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.

The plots show a close alignment of the sensitivities of banks' interest income and expense. For all banks, the slope is 0.768, while for the largest 5% it is 0.878. These numbers are close to one, as predicted. The raw correlations between income and expense betas are high: 51% for all banks and 58% for large banks.[19] Expense betas thus explain a large proportion of the variation in income sensitivities across banks.

We further examine the impact of this tight matching on the interest sensitivity of bank profitability. As in the aggregate analysis, we measure profitability as ROA (net income divided by assets). ROA can be derived from NIM (interest income minus interest expense) by subtracting loan losses and non-interest expenses (e.g. salaries and rent) and adding non-interest income (e.g. fees). We estimate ROA betas in the same way as expense and income betas (see (7)), except we use year-over-year ROA changes to account for seasonality.[20]

[19] The bin scatter plot looks noisier for large banks because there are 95% fewer observations in each bin.

[20] The seasonality is due to the fact that banks tend to book certain non-interest income and expenses in

The bottom panels of Figure 5 show that bank profitability is largely unexposed to interest rate changes. ROA betas are close to zero, both among all banks and large banks. Their relationship with expense betas among all banks is flat even though the matching coefficient for this group is a bit below one. This indicates that non-interest items provide just the right offset to make profitability unexposed. Among large banks, ROA betas are slightly lower for high-expense beta banks (the slope of the relationship is -0.191). However, the relationship is noisy and as the panel regressions below show, a more precise estimate is very close to zero. Thus, the tight matching of interest expense and income betas effectively insulates bank profitability from interest rate changes.

To get an all-inclusive measure of exposure, we analyze banks' stock returns, which price in changes in future ROA. We obtain the daily stock returns of all publicly listed banks and use them to compute FOMC betas as we did in Figure 1.[21] Specifically, we regress each bank's stock return on the change in the one-year Treasury rate over a two-day window around scheduled FOMC announcements between 1994 and 2008. We then merge the FOMC betas with the interest expense and income betas. The merged sample contains 878 publicly listed banks. The average FOMC beta is -1.40, which is similar to the industry-level FOMC beta in Figure 1.

Figure 6 presents the result as bin scatter plots of FOMC betas against interest expense and income betas, and against asset and liabilities duration (using repricing maturity as a proxy). 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 view that maturity mismatch exposes banks to interest rate risk, FOMC betas should decline by 10 for every additional year of asset duration.

Contrary to this standard view, the relationship between FOMC betas and all four sorting variables is flat. If anything, FOMC betas rise toward zero as asset duration increases and income betas fall, but the effects are small and insignificant.[22] Figure 6 thus confirms our result for ROA, which showed that interest rate exposure is equally low throughout the

the fourth quarter. Our results are robust to ignoring it. The panel regressions in particular include time fixed effects which also take out any seasonality.

[21]We thank Anna Kovner for providing the list of publicly listed banks.

[22]English, den Heuvel, and Zakrajsek (2012) similarly find that banks with a larger maturity gap have a dampened exposure to monetary policy.

distribution of banks. This result is consistent with our framework where banks are able to avoid interest rate risk even as they engage in maturity transformation.

V.C Panel analysis

In this section we use panel regressions to obtain precise estimates of interest rate sensitivity matching. Panel regressions use all of the variation in the data whereas cross-sectional regressions average some of it out. Panel regressions also implicitly give more weight to banks that have more observations, leading to more precise estimates. Finally, they allow us to include time fixed effects to control for common trends.

We implement the panel analysis in two stages. The first stage estimates a bank-specific effect of Fed funds rate changes on interest expense using the following OLS regression:

$$\Delta IntExp_{i,t} \quad = \quad \alpha_i + \eta_t + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta FedFunds_{t-\tau} + \epsilon_{i,t} \tag{8}$$

where $\Delta IntExp_{i,t}$ is the change in the interest expense rate of bank i from from time t to $t+1$, $\Delta FedFunds_t$ is the change in the Fed funds rate from t to $t+1$, and α_i and η_t are bank and time fixed effects. Unlike the cross-sectional regression where we simply summed the lag coefficients, here we utilize them fully to construct the fitted value $\Delta \widehat{IntExp}_{i,t}$. This fitted value captures the predicted change in bank i's interest expense rate following a Fed funds rate change.

The second stage regression tests for matching by asking if banks with a higher predicted change in interest expense experience a higher interest income change. Specifically, we run the following OLS regression:

$$\Delta IntInc_{i,t} \quad = \quad \lambda_i + \theta_t + \delta \Delta \widehat{IntExp}_{i,t} + \varepsilon_{i,t}. \tag{9}$$

where $\Delta IntInc_{i,t}$ is the change in bank i's interest income rate from time t to t+1, $\Delta \widehat{IntExp}_{i,t}$ is the predicted change in its interest expense rate from the first stage, and λ_i and θ_t are bank and time fixed effects. The coefficient of interest is δ, which captures the matching of income and expense rate changes. It is the analog to the slope coefficient in the cross-sectional test. In some specifications, we replace the time fixed effects with an explicit control for the Fed funds rate change and its three lags, $\sum_{\tau=0}^{3} \gamma_\tau \Delta FedFunds_{t-\tau}$. The value of $\sum_{\tau=0}^{3} \gamma_\tau$ then gives the estimated interest income sensitivity of a bank with zero interest expense sensitivity. It is the analog to the intercept in the cross-sectional test. We double-cluster standard errors at the bank and quarter level.

Table 2 presents the panel regression results. Columns (1) and (2) include all banks, first with the Fed funds rate changes as controls and then with time fixed effects. The matching coefficients, 0.765 and 0.766, respectively, are again close to one and very similar to the cross-sectional estimates.[23] This shows that the matching is not driven by some type of common time series variation. The sum of the coefficients on Fed funds rate changes, $\sum_{\tau=0}^{3} \gamma_\tau$, is very small (0.093), showing that a bank with zero interest expense sensitivity has a near-zero interest income sensitivity.

Columns (3) to (8) report results for the largest 10%, 5%, and 1% of banks. Here the coefficients are almost exactly one with 1.012 for the top 10%, 1.114 for the top 5%, and 1.096 for the top 1%. None of the estimates are more than one and a half standard errors from one, hence we cannot reject the strong hypothesis of one-to-one matching. This is despite the fact that the double-clustered standard errors are quite small. The high statistical power allows us to provide a relatively precise estimate even for the smallest sub-sample of the largest 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 shows that a bank with insensitive interest expenses is expected to have insensitive interest income, i.e. to hold only long-term fixed-rate assets.

Extrapolating these estimates in the other direction, 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 a rate close to the Fed funds rate and do not engage in maturity transformation. The ability of our estimates to capture the structure of money market funds out of sample shows a high degree of external validity.

Table 3 presents results for the interest sensitivity of banks' ROA. We use the same two-

[23] A coefficient of 0.765 implies that the sensitivity of NIM is $(0.765 - 1) = -0.235$. Hence, by construction we find a coefficient of -0.235 if we estimate regression (9) using the change in NIM as the outcome variable.

stage procedure but replace the change in interest income in equation (9) with the change in ROA. The coefficients are extremely close to zero (ranging from -0.032 to 0.000) and statistically insignificant across all sub-samples. They are unchanged whether we control for Fed funds rate changes (odd-numbered columns) or include time fixed effects (even-numbered columns). These results imply that non-interest income and expenses are largely insensitive to interest rate changes, consistent with our model.[24]

Taken together, Tables 2 and 3 provide strong evidence that banks match the interest rate sensitivities of their income and expenses. 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 almost fully insulated from interest rate changes.

V.D Robustness

Operating costs and fee income. In the model banks' operating costs are insensitive to interest rate changes and hence resemble a long-term fixed-rate liability. As we noted above, the results in Figure 5 and Tables 2 and 3 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 expenses and income.

Banks have substantial operating expenses: on average non-interest expenses exceed non-interest income by 257 bps of assets per year. We analyze their three main categories: total salaries (167 bps), total expenditure on premises or rent (46 bps), and deposit fee income (40 bps). For each category, we estimate interest rate betas as in equation (7).

The results are presented as bin scatter plots in Figure A.3, and are constructed in the same manner as Figure 5. The top panel shows that the betas of total salaries 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. The results are similar for rents and deposit fee income. These findings show that non-interest income and expenses 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

[24] In the robustness section we show directly that the main categories of banks' operating costs are insensitive to interest rate changes.

doing so, they would give up earning the term premium. While our matching results imply that there is no need to do so, it is useful to look at derivatives hedging directly.

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 2016), we find that the overwhelming majority of banks (92.9%) do not use any interest rate derivatives. This is not surprising under our framework since banks do not need derivatives to hedge. Larger banks are somewhat more likely to use interest rate derivatives, yet even among the top 10%, 61.6% report zero notional amounts.

Appendix Table A.2 presents the regression results. Columns 1 and 2 include all banks with non-missing derivatives amounts since 1995. As expected, the matching coefficients are close to one and very similar to Table 2. Columns 3 and 4 show nearly identical coefficients for banks with zero derivatives amounts. The coefficients for the derivatives users in columns 5 and 6 are also close to one, albeit slightly larger. Although the difference is small, the fact that the estimate increases above one, which indicates that these banks hold slightly too few long-term assets, may explain the puzzling finding in Begenau, Piazzesi, and Schneider (2015) that banks appear to use derivatives to increase their interest rate exposure.

Bank holding companies. Our main analysis uses commercial bank data from the Call Reports. As a simple robustness check, we rerun Table 2 using regulatory data at the bank holding company level, which is available since 1986. Table A.3 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 Sensitivity matching and bank assets

In this section we analyze how banks implement sensitivity matching by looking at the characteristics of their assets.

VI.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 proxy for duration.[25] The left panel of Figure 7 shows a bin 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 estimated duration than banks with high expense betas. The slope of the relationship is -3.662 years, which is on the order of the average duration of bank assets. As a result, while a bank with an expense beta of 0.1 has a predicted duration of 4.7 years, a bank with an expense beta of 1 is predicted to have a duration of only 1 year. This again describes money market funds, which are not in our sample but are nevertheless in line with our estimates.

The right panel in Figure 7 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 0.193). Overall, Figure 7 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 maturity by running panel regressions of the form

$$RepricingMaturity_{i,t} = \alpha_t + \delta\beta_i^{Exp} + \gamma X_{i,t} + \epsilon_{i,t}, \tag{10}$$

where $RepricingMaturity_{i,t}$ is the average repricing maturity of bank i's loans and securities

[25] Specifically, we use the repricing maturity of banks' loans and securities, for which we have detailed data since 1997. The remaining categories are mostly short-term, including cash and Fed funds sold and repurchases bought under agreements to resell.

at time t, β_i^{Exp} is its interest expense beta, α_t are time fixed effects, and $X_{i,t}$ are a set of controls. The controls we consider are the wholesale funding share (large time and brokered deposits plus Fed funds purchased and repo), the equity ratio, and size (log assets). As before, we double-cluster standard errors at the bank and quarter level.

Panel A of Table 4 presents the regression results for the sample of all banks. From column 1, the univariate coefficient on the interest expense beta is -3.951, which is similar to the cross-sectional coefficient in Figure 7 and highly significant. The coefficient remains stable and actually increases slightly as we add in the control variables in columns (2) to (4). Column (5) runs a horse race between all right-hand variables. The coefficient on the interest expense beta is -4.738, hence its explanatory power for repricing maturity is even stronger once we control for bank characteristics.

Panel B of Table 4 repeats this analysis for the largest 5% of banks. Even though this sample has only 267 banks over 67 quarters (and double-clustered standard errors), the relationship between interest expense betas and repricing maturity is strong and clear. We find that the univariate coefficient is -4.676, which is similar to the full sample. The effect rises to -6.136 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 maturity transformation if its interest expenses rose one-for-one with the Fed funds rate.

VI.B Asset composition

We can get a better understanding of how banks obtain duration by looking at the composition of their assets. From Table A.1, a primary way to obtain duration is by investing in securities, which in aggregate have an average repricing maturity of 8.8 years versus 3.8 years for loans.[26] Given these large differences, and given our results on duration, we expect banks with low expense betas to hold a larger share of securities.

Table 5 presents the results of panel regressions similar to (10) 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

[26] The higher repricing maturity of securities is due to the fact that many are linked to mortgages.

share. The stand-alone coefficient in column (1) is -0.352 while the multivariate one in column (5) is -0.212. These numbers are large relative to the average securities share in Table 1, which is 0.246, and their sign is as predicted. Panel B repeats the analysis for the largest 5% of banks. The coefficients are very similar (-0.314 in column (1) and -0.264 in column (5)), and again highly significant. By contrast, except for size, the control variables either lose their significance or see their signs flip. Thus, there is a robust negative relationship between interest expense betas and banks' securities holdings, which shows that banks with low expense betas obtain duration by holding more securities.[27]

This result is especially useful because it allows us to rule out an alternative explanation for our duration 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. 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—shows that liquidity risk does not drive our results.

VI.C Sensitivity matching within the securities portfolio

Our model predicts that banks actively match the interest sensitivities of their income and expenses 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 (2014) find that banks have market power over lending. Although market segmentation does not explain why we see one-to-one matching, we nevertheless test it further.

We do so by looking at the interest rate sensitivity of banks' securities holdings. Securities are by definition traded in an open market and hence unaffected by market segmentation. Thus, under the market segmentation interpretation we should not see matching between

[27] Replacing the securities share with the 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 83% of bank assets.

banks' expense betas and the income betas of their securities holdings. To implement this idea, we rerun our main matching test using the two-stage procedure in equations (8)–(9), but with banks' securities interest income as the second-stage outcome variable. While we no longer expect a coefficient equal to one (one-to-one matching applies to the balance sheet as a whole, not necessarily to its components), our model still predicts positive matching between expense betas and securities income betas.

Table 6 presents the results for the sample of all banks. As columns (1) and (2) show, there is strong evidence of matching between securities interest income and interest expense. The coefficients are 0.584 and 0.570, respectively, and highly significant. Columns (3) to (8) look at various sub-categories of securities. Since banks sometimes retain some self-originated securities, we get a cleaner test by looking only at Treasury securities and agency debt, 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) show the same for mortgage-backed securities (MBS) and other securities.

Table 7 repeats the analysis of Table 6 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 expenses using securities. Overall, the results in Tables 6 and 7 support the view that banks actively match their interest rate exposures.

VII Market power and sensitivity matching

Our model predicts that banks with more market power in retail deposit markets have lower interest expense betas, and that they match these 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, and then whether banks match these differences with their income betas.

We use three sources of geographic variation in market power that are progressively more refined. We embed each source within the same two-stage empirical framework we used in

Section V (see (8) and (9)). Specifically, we run

$$\Delta IntExp_{i,t} = \alpha_i + \eta_t + \sum_{\tau=0}^{3} \left(\beta_\tau^0 + \beta_\tau \times MP_{i,t}\right) \Delta FedFunds_{t-\tau} + \epsilon_{i,t} \quad (11)$$

$$\Delta IntInc_{i,t} = \lambda_i + \theta_t + \delta \Delta \widehat{IntExp}_{i,t} + \varepsilon_{i,t}. \quad (12)$$

where $\Delta IntExp_{i,t}$ is the change in the interest expense rate of bank i from from time 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 difference with the earlier regressions is that we now restrict the sensitivity coefficients to be functions of a given source of variation in market power $MP_{i,t}$. In the first stage, we are interested in the relationship between market power and interest expense sensitivity, given by $\sum_{\tau=0}^{3} \beta_\tau$. In the second stage, we are interested in the matching coefficient δ. We again double-cluster standard errors by bank and quarter.

VII.A Market concentration

Our first source of variation in market power is local market concentration. We use the FDIC data to calculate a Herfindahl (HHI) index for each zip code by computing each bank's share of the total branches in the zip code and summing the squared shares. We then create a bank-level HHI by averaging the zip-code HHIs of each bank's branches, using the bank's deposits in each zip code as weights. The resulting average bank HHI is 0.408 and its standard deviation is 0.280, indicating substantial geographic variation.

Figure 8 shows that there is a negative relationship between market concentration and interest expense betas. Banks operating in zip codes with zero concentration have an average interest expense beta of 0.37 versus 0.29 for those in highly concentrated zip codes. Note that even though there is substantial variation, interest expense betas are well below one everywhere. Hence banks appear to have significant market power in all areas, which allows them to justify the high costs of operating a deposit franchise.

The first two columns of Table 8 present the results of the two-stage estimation. Column (1) controls for Fed funds rate changes directly, while column (2) includes time fixed effects. The first-stage estimates in the top panel show that market concentration is significantly negatively related to the sensitivity of banks' interest expenses, as predicted. The first-stage coefficients are -0.047 and -0.059 in columns (1) and (2), respectively, which is similar to the slope of the cross-sectional regression line in Figure 8.

The bottom panel of Table 8 shows that the variation in expense sensitivity induced by market concentration is matched on the income side. The second-stage coefficients are 1.264 and 1.278 in columns (1) and (2), respectively, which is a bit higher than our earlier estimates but still not significantly different from one. As column (1) shows, the direct effect of Fed funds rate changes is zero, indicating that a bank with zero expense sensitivity is predicted to have zero income sensitivity, i.e. hold only long-term fixed-rate assets.

To ensure that our results are robust to alternative definitions of a local deposit market, we rerun the same analysis with a county-level HHI instead of a zip-code-level one. The results are in columns (3) and (4). The first-stage estimates are almost identical to the zip-code-level ones, and the matching coefficients are now even closer to one. Thus, the results in Table 8 support the market power mechanism of our model.

VII.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. Because retail deposits are insured, and hence immune to runs they also allow us to further show that our results cannot be explained by liquidity risk.

The Ratewatch data contains 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:

$$DepRate_{b,i,c,t} = \alpha_b + \gamma_i + \delta_c + \eta_t + \sum_c \beta_c \times FedFunds_t + \varepsilon_{b,i,c,t}, \tag{13}$$

where $DepRate_{b,i,c,t}$ is the deposit rate of branch b of bank i in county c on date t. We run (13) 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. We use this bank-level average retail deposit beta as our market power proxy in the two-stage procedure (11)–(12). Note that the bank-level retail deposit beta does not use information about the bank's pricing of deposits. Instead, it is based on the average market power of other banks operating in the same area.

The first two columns of Table 9 present the results. The first-stage coefficients are highly significant and equal to 0.550 and 0.565 in columns (1) and (2), respectively. This shows that retail deposit betas strongly predict banks' overall interest expense sensitivities. The second stage shows the matching. The coefficients are 1.259 and 1.264 in columns (1) and (2), respectively, again a bit higher than one but not statistically different. Thus, variation in retail deposit betas generates variation in expense sensitivities, which banks in turn match with their income sensitivities. These two results correspond to the two key ingredients of the market power mechanism of our model.

As our third source of variation, we go a step further and focus in on 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 (13)). Thus, these estimates are identified by comparing only 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 columns (3) and (4) of Table 9. As the first-stage estimates show, the within-bank retail deposit betas have a significant and sizable impact on banks' overall interest expense sensitivity. 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 in bank-level 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 1.185 to 1.186 in columns (3) and (4), respectively, which is again very close to one. These results show that differences in market power create variation in expense betas that banks match one-for-one on the income side.

VIII Conclusion

The conventional view is 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 expenses 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 expenses banks are largely insulated from this effect. Banks' maturity mismatch is also a source of concerns about financial stability. This has led to calls for narrow banking, the idea that deposit-issuing institutions should only hold short-term assets. Our results imply that so long as banks have market power, narrow banking would not achieve its purpose and could actually reduce financial stability.

More broadly, our results provide an explanation for the co-existence of deposit-taking and maturity transformation. Unlike the conventional wisdom, which views this co-existence as a source of risk and instability, this explanation highlights its enduring stability.

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Table 1: **Bank characteristics and expense beta**

This table provides summary statistics on bank characteristics. The sample in Panel A are all U.S. commercial banks from 1984 to 2013. Panel B restricts the sample to the largest 5% of banks. Interest expense betas are calculated by regressing the change in a bank's interest expense on the contemporaneous and three previous quarterly changes in the Fed funds rate. Interest income and ROA betas are calculated analogously. A bank must have at least 20 quarterly observations for its beta to be reported and the betas are winsorized at the 5% level. Columns (1) and (2) report the sample mean and standard deviation. Columns (3) and (4) report averages for banks with above and below median expense beta.

Panel A: All banks

	All		Low beta	High beta
	(1)	(2)	(3)	(4)
Interest rate sensitivity				
Interest expense beta	0.360	(0.096)	0.283	0.436
Interest income beta	0.379	(0.147)	0.320	0.437
ROA beta	0.039	(0.150)	0.038	0.040
Bank characteristics				
Asset repricing maturity	3.360	(1.580)	3.588	3.088
Liabilities repricing maturity	0.441	(0.213)	0.462	0.416
Log assets	4.232	(1.275)	3.969	4.494
Loans/Assets	0.585	(0.132)	0.566	0.603
Securities/Assets	0.246	(0.131)	0.267	0.225
Core Deposits/Assets	0.732	(0.115)	0.751	0.713
Equity/Assets	0.097	(0.036)	0.101	0.091
Observations	18,552		9,276	9,276

Panel B: Top 5%

	All		Low beta	High beta
	(1)	(2)	(3)	(4)
Interest rate sensitivity				
Interest expense beta	0.448	(0.085)	0.379	0.518
Interest income beta	0.446	(0.135)	0.387	0.505
ROA beta	0.017	(0.121)	0.035	0.001
Bank characteristics				
Asset repricing maturity	4.001	(2.069)	4.551	3.349
Liabilities repricing maturity	0.400	(0.257)	0.411	0.401
Log assets	7.565	(1.231)	7.359	7.771
Loans/Assets	0.628	(0.117)	0.625	0.631
Securities/Assets	0.201	(0.103)	0.220	0.182
Core Deposits/Assets	0.646	(0.161)	0.684	0.608
Equity/Assets	0.078	(0.029)	0.079	0.077
Observations	860		430	430

Table 2: **Interest sensitivity matching**

This table provides estimates of the matching of interest income and expense sensitivities. The results are from the following two-stage ordinary least squares regression:

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

where $\Delta IntExp_{i,t}$ and $\Delta IntInc_{i,t}$ are the changes in interest expense and interest income rates of bank i at time t, $\Delta FedFunds_t$ 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. Top 10% are the 10% largest banks by average rank of 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 2013. Standard errors are clustered at the bank and quarter level.

Δ Interest income rate

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\widehat{IntExp}$	0.765***	0.766***	1.012***	1.012***	1.114***	1.111***	1.096***	1.089***
	(0.033)	(0.034)	(0.083)	(0.083)	(0.099)	(0.099)	(0.068)	(0.076)
$\sum \gamma_\tau$	0.093***		0.003		−0.053		−0.065	
	(0.031)		(0.042)		(0.050)		(0.050)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	1,126,023	1,126,023	89,832	89,832	44,584	44,584	9,833	9,833
Bank clusters	18,552	18,552	1,733	1,733	860	860	157	157
Time clusters	119	119	119	119	119	119	119	119
R^2	0.089	0.120	0.118	0.151	0.120	0.153	0.109	0.150

Table 3: **The interest sensitivity of ROA**

This table provides estimates of the interest rate sensitivity of return on assets (ROA). The results are from the following two-stage ordinary least squares regression:

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

where $\Delta IntExp_{i,t}$ and $\Delta ROA_{i,t}$ are the changes in the interest expense rate and ROA of bank i at time t, $\Delta FedFunds_t$ 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. Top 10% are the 10% largest banks by average rank of 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 2013. Standard errors are clustered at the bank and quarter level.

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \widehat{IntExp}$	−0.018	−0.012	−0.009	0.000	−0.020	−0.013	−0.032	−0.020
	(0.014)	(0.015)	(0.015)	(0.015)	(0.022)	(0.022)	(0.044)	(0.046)
$\sum \gamma_\tau$	0.044***		0.031*		0.030		0.036	
	(0.013)		(0.016)		(0.019)		(0.033)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	1,126,023	1,126,023	89,832	89,832	44,584	44,584	9,833	9,833
Bank clusters	18,552	18,552	1,733	1,733	860	860	157	157
Time clusters	119	119	119	119	119	119	119	119
R^2	0.027	0.036	0.029	0.051	0.023	0.053	0.016	0.097

Table 4: **Maturity transformation and expense betas**

This table estimates the relationship between expense beta and asset duration. The proxy for duration is repricing maturity, calculated as the weighted average repricing maturity of loans and securities. The interest expense betas are estimated according to (7) and winsorized at the 5% level. The control variables are wholesale funding (sum of large time deposits, Fed funds purchased, repos, and brokered deposits, divided by assets), equity ratio (equity divided by assets), and log total assets. Top 5% of banks (Panel B) are the largest 5% by assets. The data are quarterly and cover all U.S. commercial banks with at least 5 years of data between 1997 to 2013. Standard errors are clustered at the bank and quarter level.

Panel A: All banks

	Repricing maturity				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−3.951***	−3.715***	−4.256***	−4.934***	−4.738***
	(0.241)	(0.238)	(0.243)	(0.246)	(0.247)
Wholesale funding ratio		−0.616***			−1.052***
		(0.180)			(0.175)
Equity ratio			−3.482***		−2.467***
			(0.485)		(0.499)
log Assets				0.238***	0.236***
				(0.017)	(0.017)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	474,391	474,391	474,391	474,391	474,391
Bank clusters	8,785	8,785	8,785	8,785	8,785
Time clusters	67	67	67	67	67
R^2	0.118	0.119	0.122	0.139	0.143

Panel B: Top 5%

	Repricing maturity				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−4.676***	−5.346***	−5.405***	−5.027***	−6.136***
	(1.323)	(1.477)	(1.285)	(1.397)	(1.489)
Wholesale funding ratio		2.260			1.886
		(1.400)			(1.321)
Equity ratio			−13.470***		−12.814***
			(1.983)		(1.858)
log Assets				0.055	0.072
				(0.078)	(0.078)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	13,445	13,445	13,445	13,445	13,445
Bank clusters	267	267	267	267	267
Time clusters	67	67	67	67	67
R^2	0.048	0.063	0.107	0.049	0.117

Table 5: **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 interest expense betas are estimated according to (7) and winsorized at the 5% level. The control variables are wholesale funding (sum of large time deposits, Fed funds purchased, repos, and brokered deposits, divided by assets), equity ratio (equity divided by assets), and log total assets. Top 5% of banks (Panel B) are the largest 5% by assets. The data are quarterly and cover all U.S. commercial banks with at least 5 years of data between 1997 to 2013. Standard errors are clustered at the bank and quarter level.

Panel A: All banks

	Securities/Assets				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−0.352***	−0.254***	−0.307***	−0.316***	−0.212***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Wholesale funding ratio		−0.255***			−0.235***
		(0.016)			(0.016)
Equity ratio			0.555***		0.500***
			(0.042)		(0.042)
log Assets				−0.008***	−0.002*
				(0.001)	(0.001)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1,090,772	1,090,770	1,090,772	1,090,772	1,090,770
Bank clusters	15,329	15,329	15,329	15,329	15,329
Time clusters	119	119	119	119	119
R^2	0.098	0.119	0.116	0.101	0.135

Panel B: Top 5%

	Securities/Assets				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−0.314***	−0.336***	−0.328***	−0.230***	−0.264***
	(0.063)	(0.064)	(0.062)	(0.058)	(0.058)
Wholesale funding ratio		0.060			0.060
		(0.041)			(0.039)
Equity ratio			−0.342**		−0.413***
			(0.160)		(0.155)
log Assets				−0.021***	−0.023***
				(0.003)	(0.003)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	42,724	42,724	42,724	42,724	42,724
Bank clusters	689	689	689	689	689
Time clusters	119	119	119	119	119
R^2	0.067	0.070	0.074	0.106	0.120

Table 6: **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 results are from the following two-stage ordinary least squares regression:

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

where $IntIncX_{i,t}$ is the change in the rate of interest income from total securities (columns (1) and (2)), Treasuries and agency debt (columns (3) and (4)), mortgage-backed securities (columns (5) and (6)), and other securities (columns (7) and (8)), $\Delta IntExp_{i,t}$ is the change in the interest expense rate of bank i at time t, $\Delta FedFunds_t$ 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. The data are quarterly and cover all U.S. commercial banks from 1984 to 2013 (columns (1) and (2)) and 1997 to 2013 (columns (3) to (8)). Standard errors are clustered at the bank and quarter level.

Δ Securities interest income rate

	Total securities		Treasuries & agency debt		MBS		Other securities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \widehat{IntExp}$	0.584***	0.570***	0.435***	0.429***	0.504***	0.489***	0.520***	0.516***
	(0.044)	(0.045)	(0.055)	(0.054)	(0.082)	(0.082)	(0.061)	(0.062)
$\sum \gamma_\tau$	0.052		0.094**		−0.028		−0.123***	
	(0.040)		(0.039)		(0.068)		(0.022)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	1,115,149	1,115,149	322,495	322,147	279,794	279,794	302,888	302,888
Bank clusters	18,448	18,448	8,918	8,918	8,054	8,054	8,450	8,450
Time clusters	119	119	51	51	51	51	51	51
R^2	0.012	0.024	0.022	0.033	0.005	0.010	0.008	0.009

Table 7: **Sensitivity matching within the securities portfolio, top 5% of banks**

This table provides estimates of the matching of the sensitivities of interest expense and interest income from securities for the largest 5% of banks by assets. The results are from the following two-stage ordinary least squares regression:

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

where $IntIncX_{i,t}$ is the change in the rate of interest income from total securities (columns (1) and (2)), Treasuries and agency debt (columns (3) and (4)), mortgage-backed securities (columns (5) and (6)), and other securities (columns (7) and (8)), $\Delta IntExp_{i,t}$ is the change in the interest expense rate of bank i at time t, $\Delta FedFunds_t$ 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. The data are quarterly and cover all U.S. commercial banks from 1984 to 2013 (columns (1) and (2)) and 1997 to 2013 (columns (3) to (8)). Standard errors are clustered at the bank and quarter level.

	Δ Securities interest income rate							
	Total securities		Treasuries & agency debt		MBS		Other securities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\widehat{IntExp}$	0.950***	0.933***	0.790***	0.792***	1.324***	1.347***	1.019***	1.035***
	(0.141)	(0.142)	(0.219)	(0.218)	(0.355)	(0.364)	(0.240)	(0.240)
$\sum \gamma_\tau$	−0.166**		−0.003		−0.395**		−0.224**	
	(0.068)		(0.103)		(0.154)		(0.104)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	44,382	44,382	8,877	8,877	9,333	9,333	9,418	9,418
Bank clusters	857	857	281	281	282	282	285	285
Time clusters	119	119	51	51	51	51	51	51
R^2	0.016	0.034	0.030	0.041	0.019	0.038	0.016	0.022

Table 8: **Market power and interest sensitivity matching**

This table estimates the effect of market power on interest rate sensitivity matching. The results are from the following two-stage ordinary least squares regression:

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

where $X_{i,t}$ is bank i's market concentration, $\Delta IntExp_{i,t}$ and $\Delta IntInc_{i,t}$ are the changes in interest expense and interest income rates of bank i at time t, $\Delta FedFunds_t$ is the change in the Fed funds rate, and $\Delta\widehat{IntExp}_{i,t}$ is the predicted value from the first stage. To calculate market concentration, we construct a Herfindahl index of bank branches at the zip code level (columns (1) and (2)) or county level (columns (3) and (4)), then average them across each bank's branches, using branch deposit as weights. Columns (2), and (4) include time fixed effects. The data are quarterly and cover all U.S. commercial banks from 1994 to 2013. Standard errors are clustered at the bank and quarter level.

	Market concentration (zip code)		Market concentration (county)	
	(1)	(2)	(3)	(4)
Stage 1:	Δ Interest expense rate			
$\sum \beta_\tau$	−0.047***	−0.059***	−0.047**	−0.065***
	(0.021)	(0.016)	(0.023)	(0.016)
R^2	0.196	0.237	0.194	0.234
Stage 2:	Δ Interest income rate			
$\Delta\widehat{IntExp}$	1.264***	1.278***	0.921***	0.838***
	(0.186)	(0.154)	(0.308)	(0.250)
$\sum \gamma_\tau$	−0.044		−0.060	
	(0.071)		(0.069)	
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
R^2	0.088	0.122	0.087	0.12
Observations	624,204	624,204	624,204	624,204
Bank clusters	13,010	13,010	13,010	13,010
Time clusters	80	80	80	80

Table 9: **Retail deposit betas and interest sensitivity matching**

This table examines the effect of retail deposit betas on interest rate sensitivity matching. The results are from the following two-stage ordinary least squares regression:

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

where $X_{i,t}$ is bank i's retail deposit beta (columns (1) and (2)) and bank i's retail deposit beta using within-bank estimation (column (3) and (4)). Retail deposit betas are calculated at the county level using Ratewatch data for interest checking, \$25k money market accounts and \$10k 12-month CDs, then averaged across branches for each bank-product (using branch deposits as weights) and finally across product for each bank. Retail deposit betas using within-bank estimation impose bank-time fixed effects in the first step of this estimation in order to purge the betas of any time-varying bank characteristics. Columns (2) and (4) include time fixed effects. The data are quarterly and cover all U.S. commercial banks from 1997 to 2013. Standard errors are clustered at the bank and quarter level.

	Retail deposit beta (across-bank)		Retail deposit beta (within-bank)	
	(1)	(2)	(3)	(4)
Stage 1:	Δ Interest expense rate			
$\sum \beta_\tau$	0.550***	0.565**	0.109***	0.110**
	(0.057)	(0.056)	(0.013)	(0.013)
R^2	0.214	0.264	0.210	0.258
Stage 2:	Δ Interest income rate			
$\Delta \widehat{IntExp}$	1.259***	1.264***	1.185***	1.186***
	(0.136)	(0.136)	(0.114)	(0.119)
$\sum \gamma_\tau$	-0.064		-0.040	
	(0.050)		(0.052)	
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
R^2	0.093	0.121	0.091	0.126
Observations	492,862	492,862	446,862	446,862
Bank clusters	10,433	10,433	9,577	9,577
Time clusters	68	68	68	68

Figure 1: **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 two-day window around FOMC meetings as in Hanson and Stein (2015). The sample includes all scheduled FOMC meetings from 1994 to 2008 (there are 113 such meetings and 5 unscheduled ones).

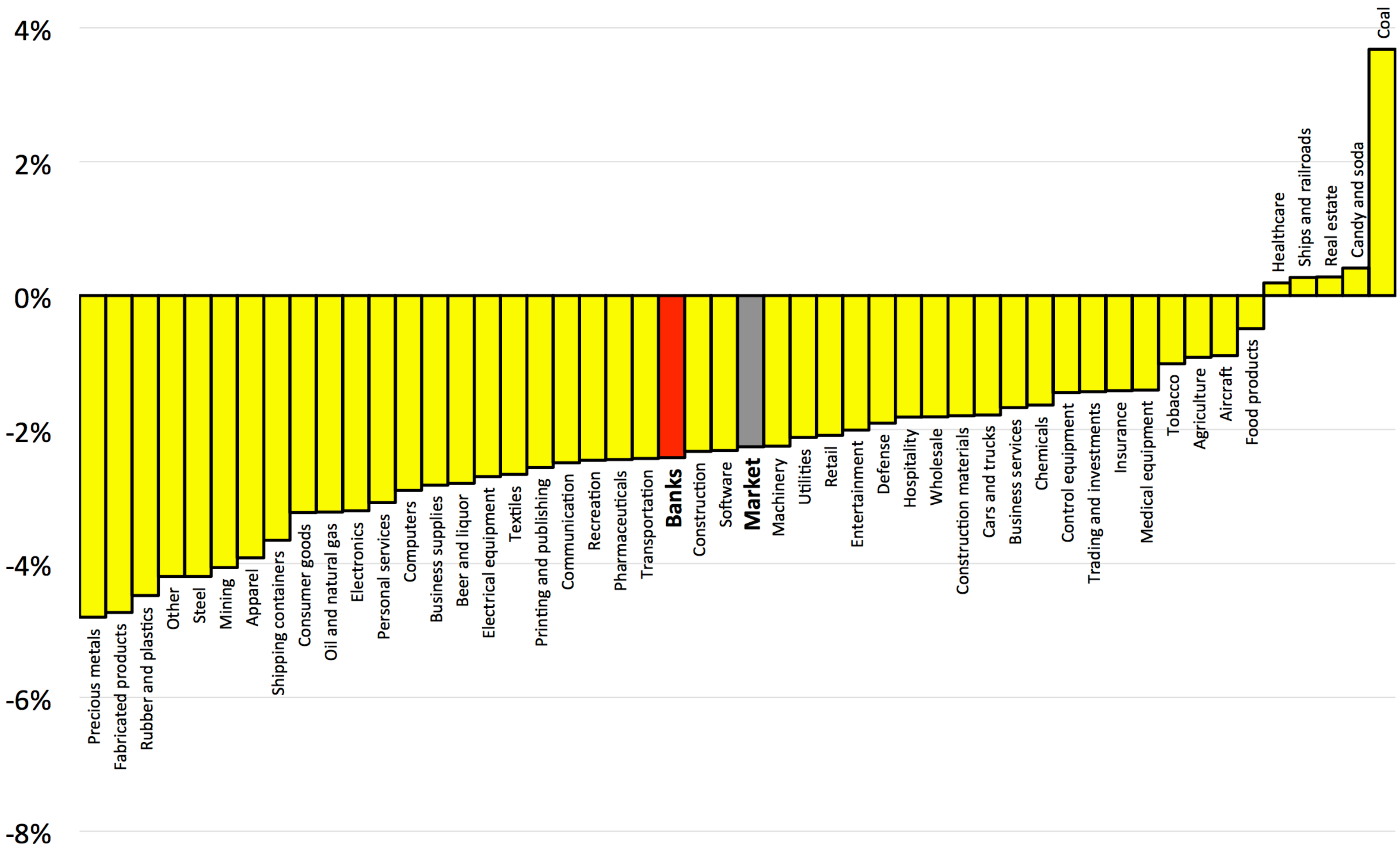
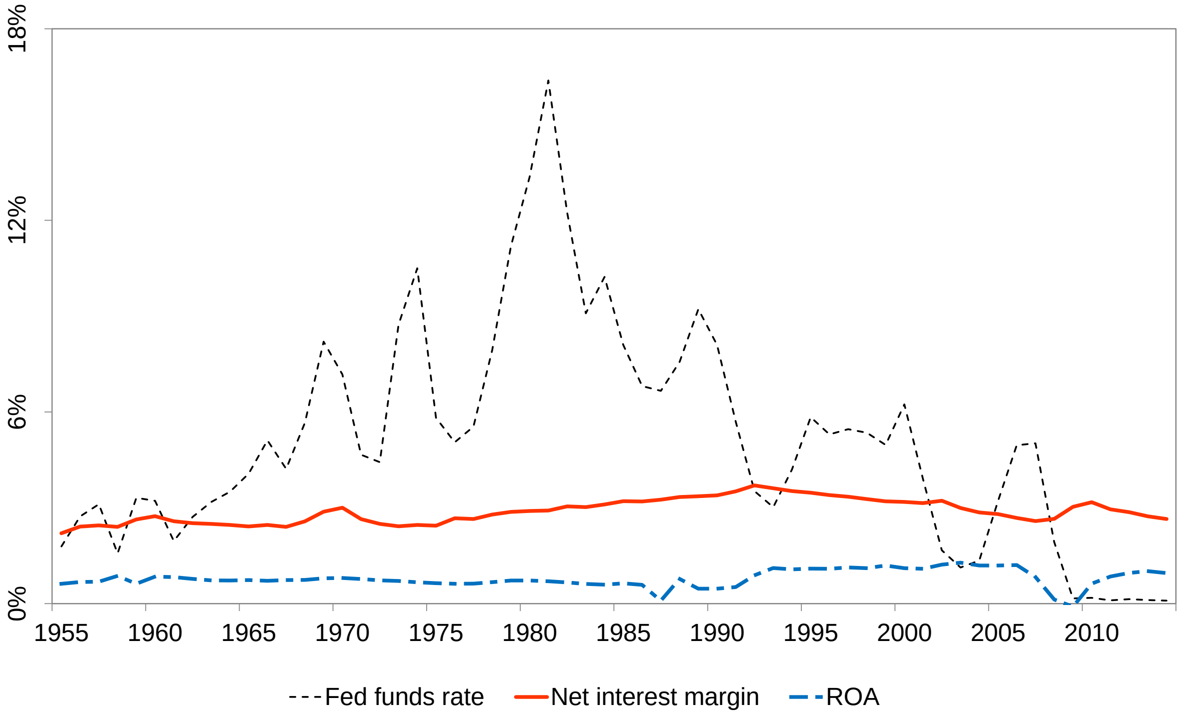


Figure 2: **Aggregate time series**

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 FDIC, 1955 to 2015.

Panel A: NIM and ROA



Panel B: Interest income and interest expense rate

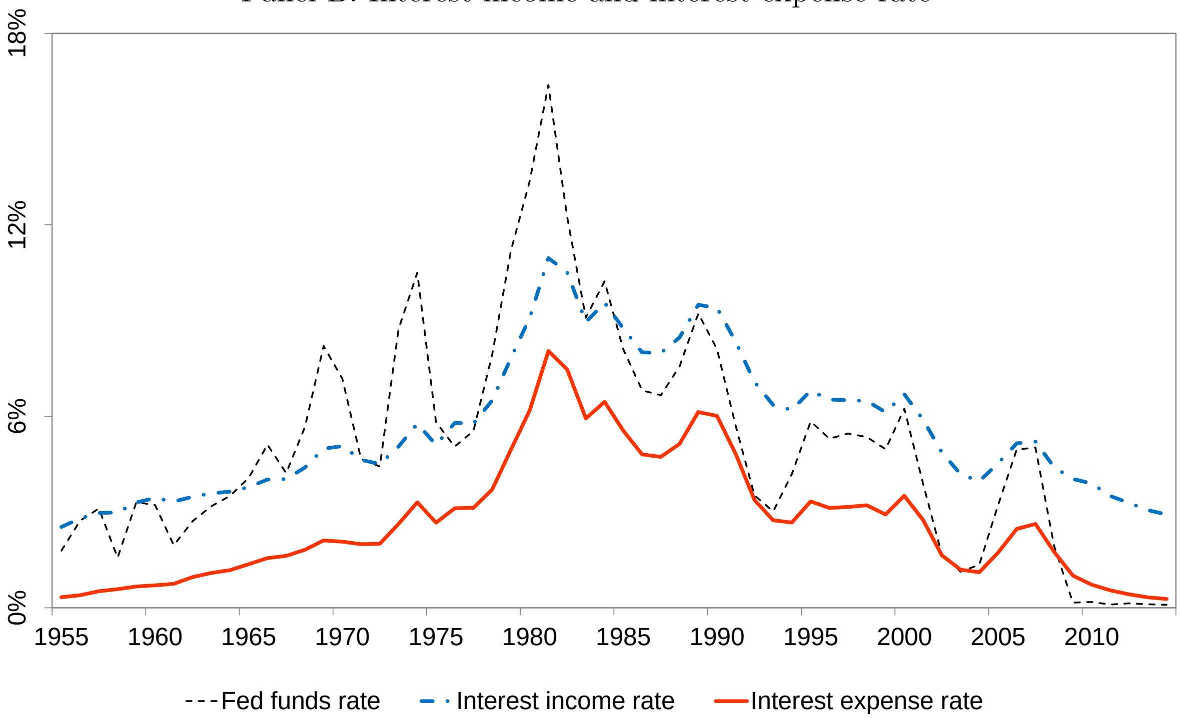


Figure 3: **Estimated duration of aggregate bank assets and liabilities**

The figure plots the repricing maturity, a 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 is from 1997 (when repricing maturity data becomes available) to 2013.

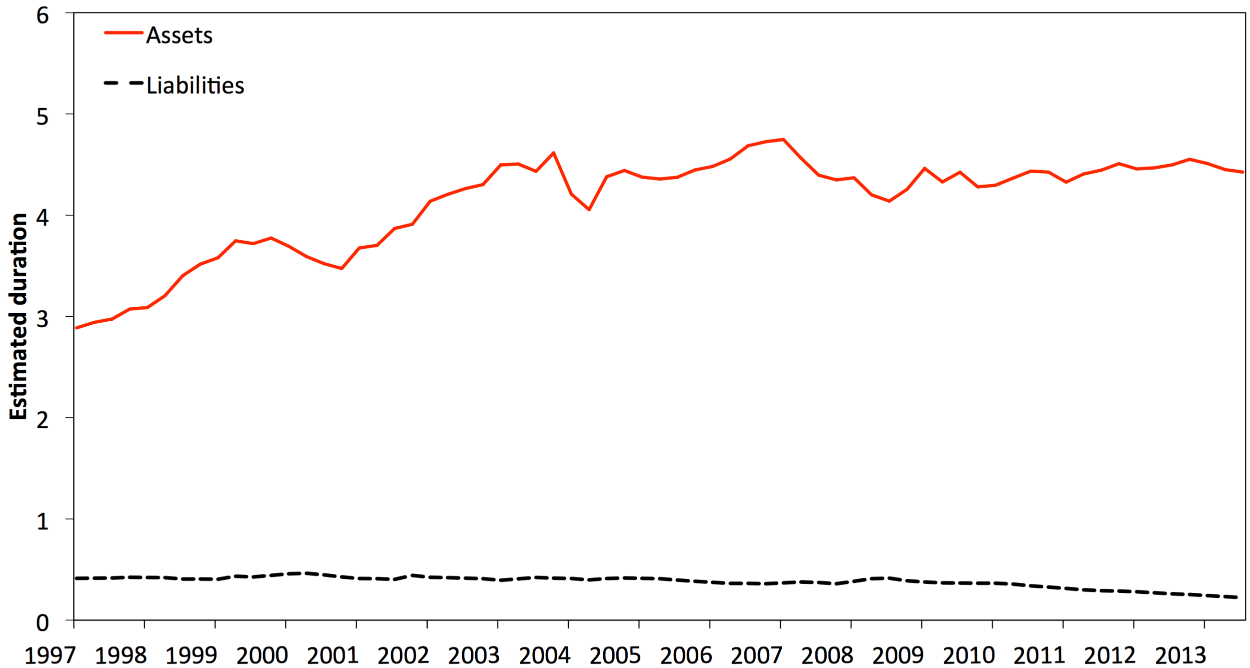
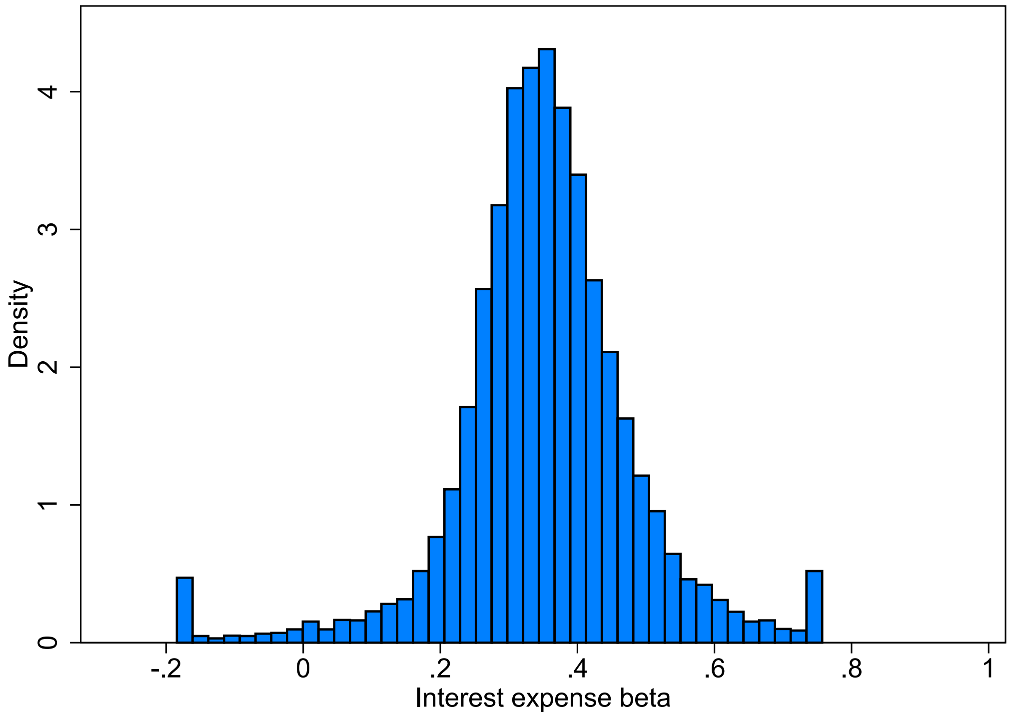


Figure 4: **The distributions of interest expense and income betas**

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 20 quarterly obervations. For this figure, the betas are winsorized at the 1% level.



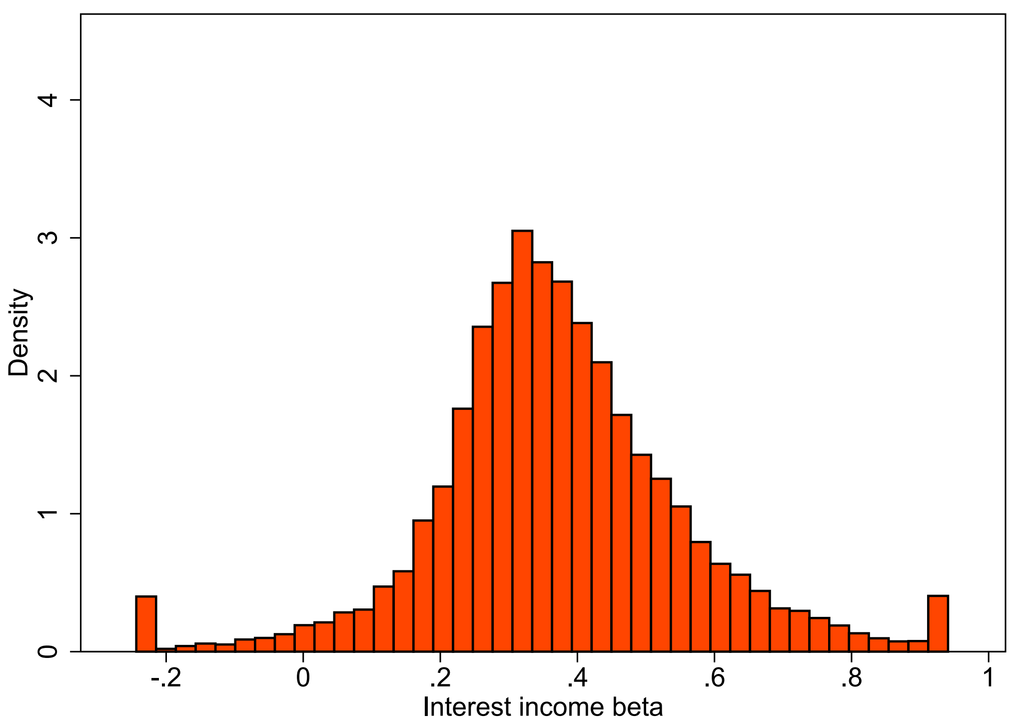


Figure 5: **Interest expense, interest income, and ROA matching**

This figure shows bin scatter plots of interest expense, interest income, and ROA betas for all banks and the largest five percent 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 20 quarterly observations are included. The betas are winsorized at the 5% level. The bin 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% percent of banks are those whose average percentile rank by assets over the sample is below the fifth percentile. The sample is from 1984 to 2013.

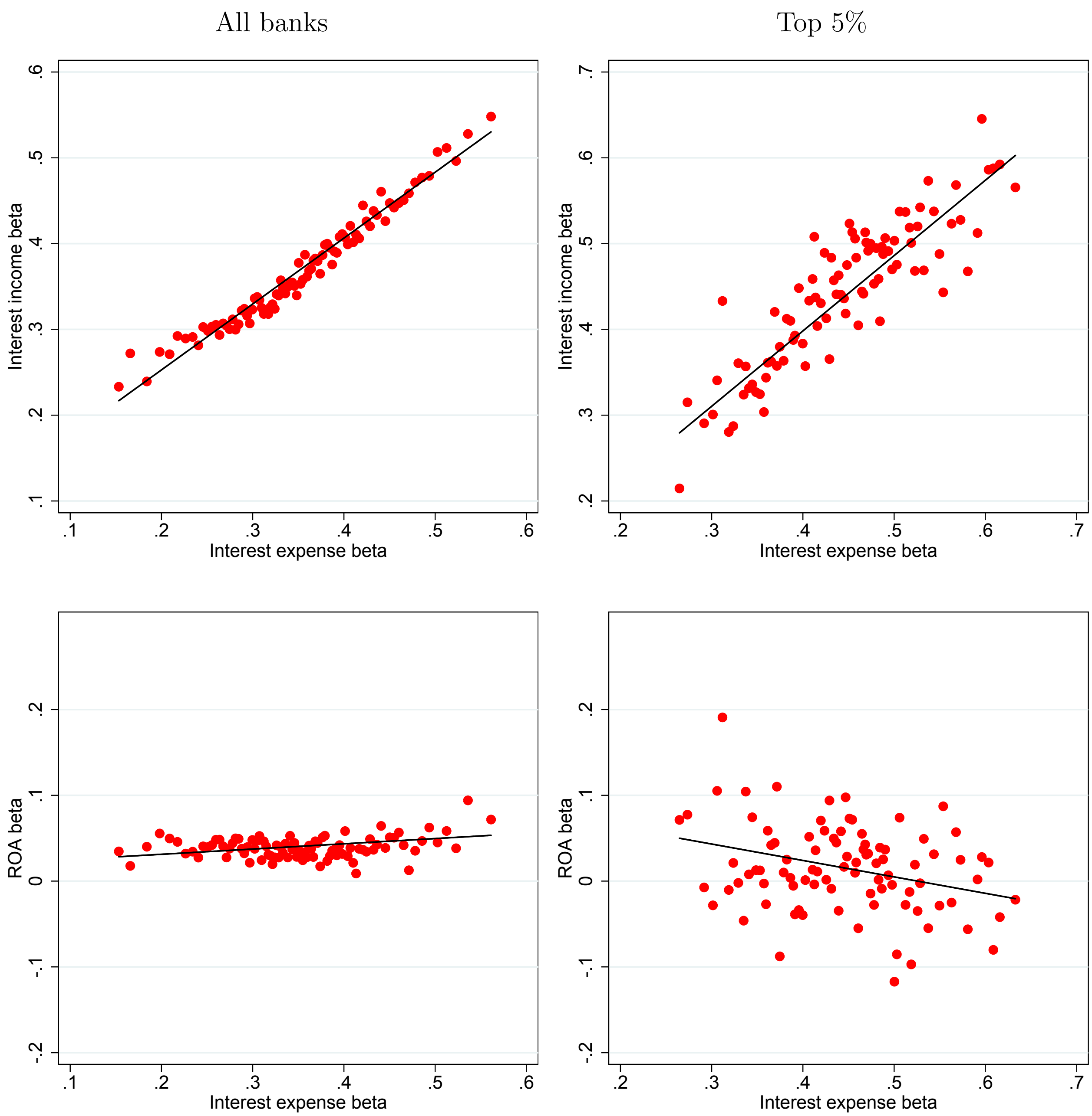


Figure 6: **Equity FOMC betas**

This figure shows bin scatter plots of banks' equity FOMC betas against their interest expense betas (top left), interest income betas (top right), asset duration (bottom left), and liabilities duration (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 two-day window around scheduled FOMC meetings. The 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 proxy for duration is repricing maturity. The sample includes all publicly listed banks with at least 20 quarterly observations. The betas are winsorized at the 5% level. The bin scatter plot groups the bank holding companies into 50 bins and plots the average FOMC beta within each bin. The sample is from 1994 to 2008.

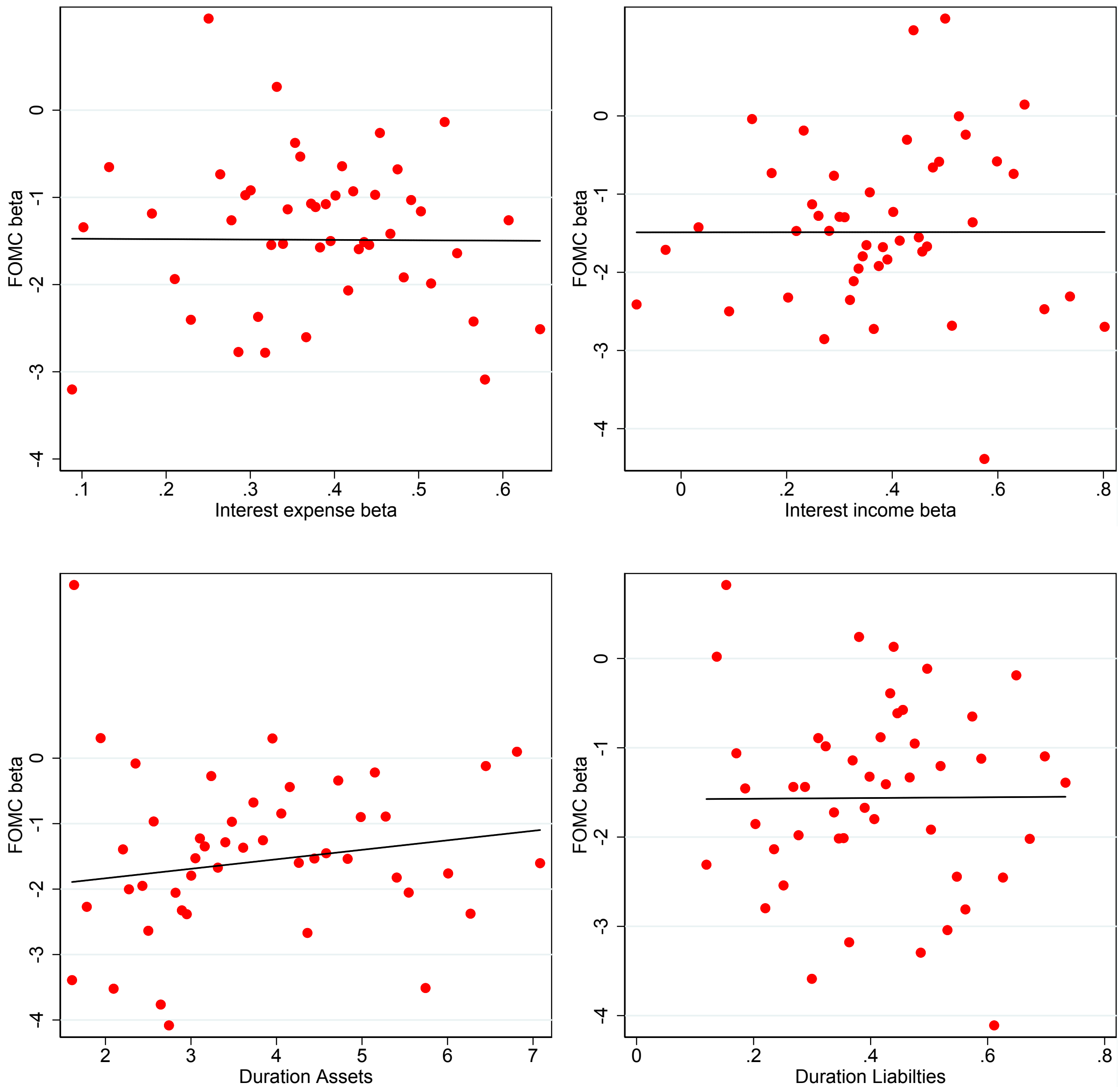


Figure 7: **Interest expense betas and asset duration**

This figure shows bin 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 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 20 quarterly observations are included and the betas are winsorized at the 5% level. The bin 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 is from 1997 to 2013.

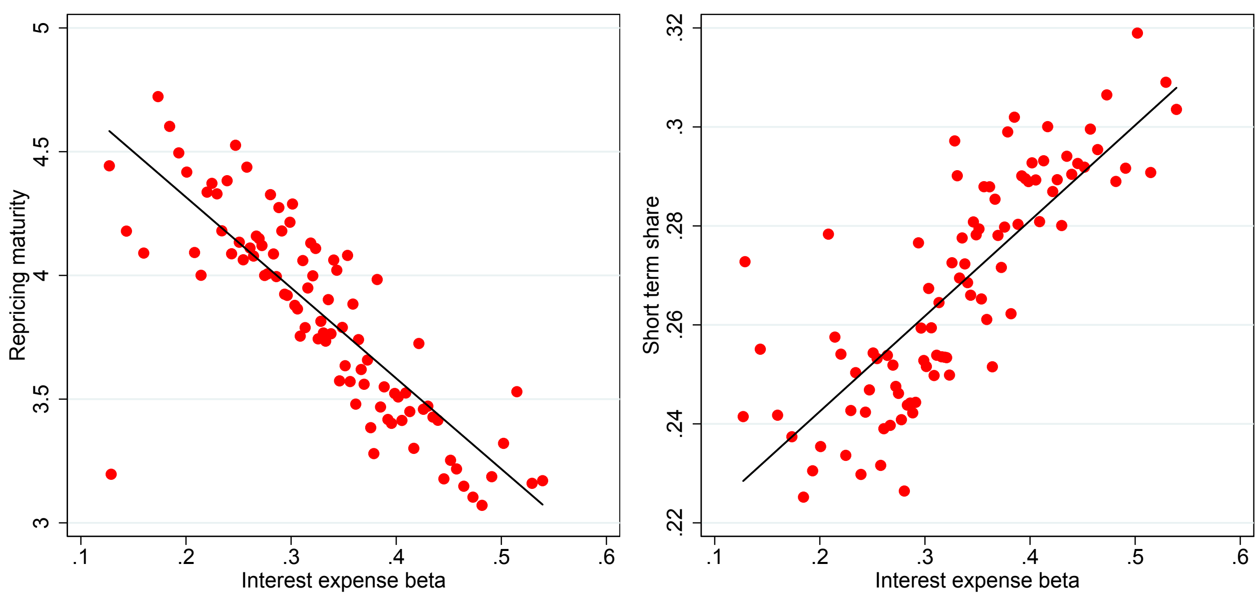
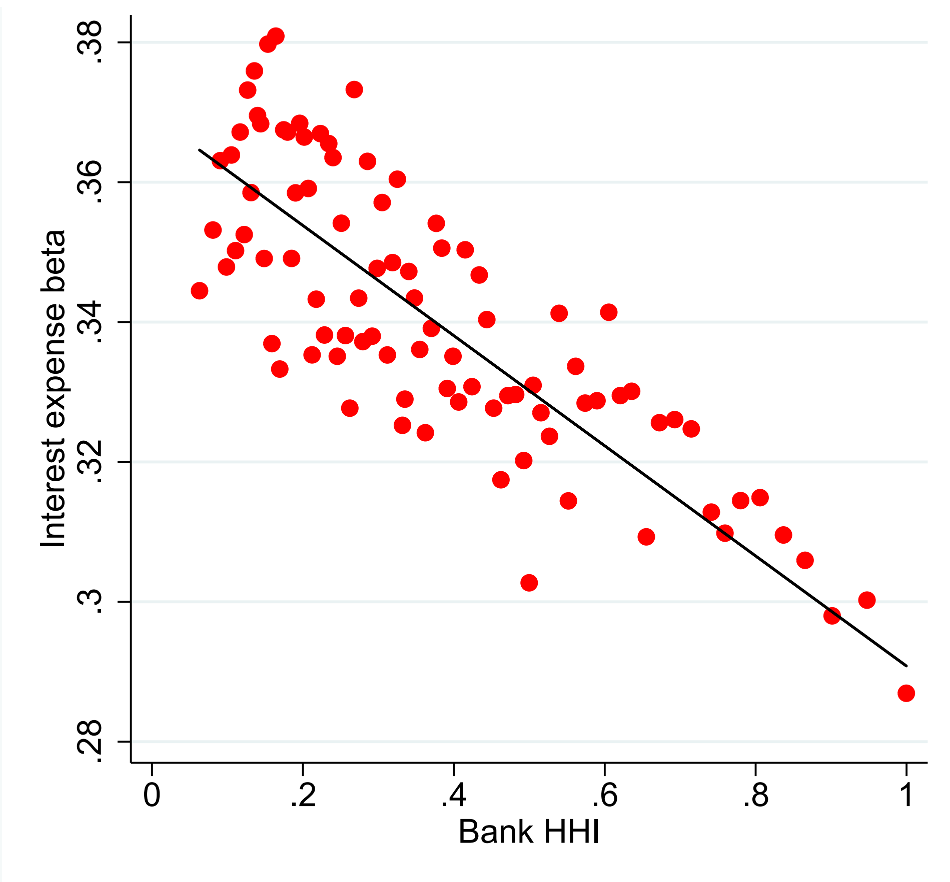


Figure 8: **Interest expense betas and market concentration**

This figure presents a bin scatter plot of interest expense betas against a bank Herfindahl (HHI) index. To calculate the bank HHI, we first calculate a zip-code HHI by computing each bank's share of the total branches in the zip code and summing the squared shares. We then create the bank HHI by averaging the zip-code HHIs of each bank's branches, using the bank's deposits in each zip code as weights. 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 20 quarterly observations are included. The betas are winsorized at the 5% level. The sample covers 1994 to 2013.



Appendix

This appendix contains supplementary tables and figures.

Table A.1: **Repricing maturity by asset category**

This table reports summary statistics on repricing maturity and asset shares. Repricing maturity is computed as the weighted average by asset category. Asset shares are total amounts in each asset category as a share of total assets. The sample are all U.S. commercial banks from 1997 to 2013 and we include all assets with reported repricing maturities (97% of total assets). Columns (1) and (2) are for the average bank. Columns (3) and (4) are for the aggregate banking system.

	Average bank		Aggregate	
	Asset Share	Repricing Maturity	Asset Share	Repricing Maturity
	(1)	(2)	(3)	(4)
Securities	23.3%	5.8	17.9%	8.8
Gov't Securities/Assets	16.8%	5.3	8.0%	6.2
RMBS/Assets	4.4%	9.0	6.2%	14.3
Other/Assets	2.1%	2.9	3.6%	5.1
Loans	61.3%	3.1	55.9%	3.8
Residential Loans	13.6%	4.8	11.2%	9.2
Other Loans	47.7%	2.6	44.7%	2.4
Cash	12.5%	0	13.9%	0
Securities + Loans + Cash	97.1%	3.5	87.7%	4.3

Table A.2: **Interest sensitivity matching and derivatives usage**

This table estimates the same regressions as in Table 2 for the sub-samples that do and do not use interest rate derivatives. Columns 1 and 2 provide results for all banks with non-missing derivatives data (this data starts in 1995). Columns 3 and 4 present results for banks that have zero exposure to derivatives. Columns 5 and 6 present results for banks that have nonzero exposure to derivatives.

Δ Interest income rate

	All banks		No derivatives		Nonzero derivatives	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widehat{IntExp}$	1.108***	1.114***	1.096***	1.104***	1.305***	1.323***
	(0.056)	(0.055)	(0.055)	(0.054)	(0.071)	(0.073)
$\sum \gamma_\tau$	−0.011		−0.007		−0.090**	
	(0.030)		(0.029)		(0.039)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Obs.	563,955	563,955	521,021	521,021	37,163	37,163
Bank clusters	12,073	12,073	11,754	11,754	2,192	2,192
Time clusters	75	75	75	75	75	75
R^2	0.137	0.172	0.144	0.180	0.219	0.246

Table A.3: **Interest sensitivity matching for bank holding companies (BHC)**

This table examines whether bank holding companies match the interest rate sensitivity of their income and expenses. The results are from the following two-stage ordinary least squares regression of interest income rates on interest expense rates:

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

Columns (2), (4), (6), and (8) include time fixed effects. Top 10% of banks are those that have a top-10% average rank by assets over the sample. Top 5% and top 1% of banks are defined analogously. The data are quarterly and cover all U.S. BHCs from 1989 to 2013. Standard errors are clustered at the bank and quarter level.

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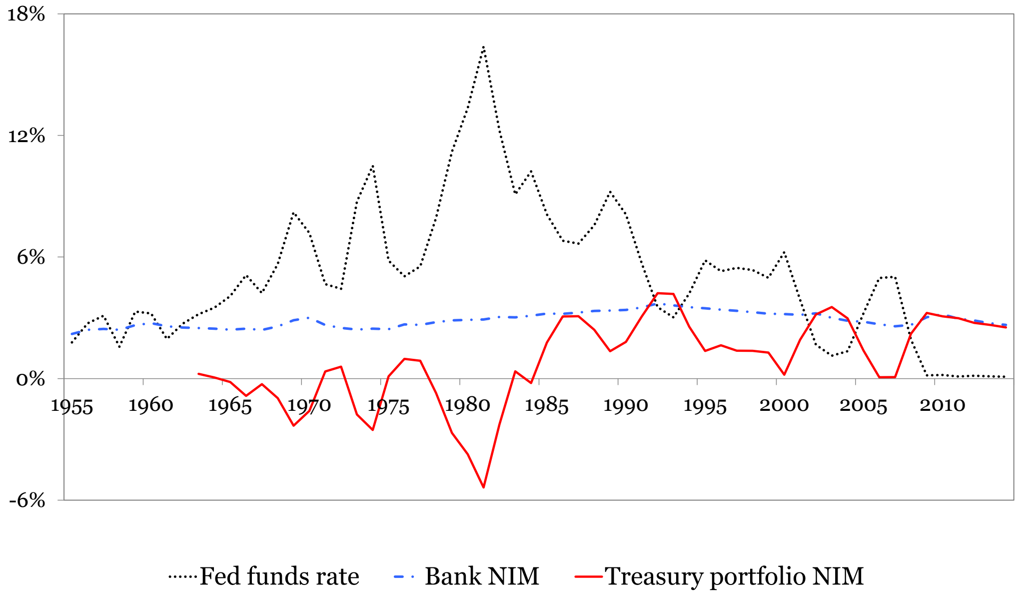
Δ Interest income rate

	All BHC		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\widehat{IntExp}$	1.063***	1.055***	1.117***	1.106***	1.117***	1.105***	1.071***	0.995***
	(0.071)	(0.070)	(0.118)	(0.120)	(0.177)	(0.182)	(0.145)	(0.153)
$\sum \gamma_\tau$	−0.026		−0.098*		−0.108		−0.089	
	(0.031)		(0.056)		(0.090)		(0.090)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	143,013	143,013	13,223	13,223	6,761	6,761	1,218	1,218
Bank clusters	4,232	4,232	322	322	162	162	28	28
Time clusters	108	108	108	108	108	108	108	108
R^2	0.175	0.217	0.159	0.213	0.151	0.219	0.165	0.368

Figure A.1: **Net interest margin of a simulated Treasury portfolio**

The figure plots the net interest margin (Panel A) and interest income and interest expense (Panel B) for banks and a simulated portfolio of Treasury bonds constructed to have the same duration mismatch as banks. The simulated portfolio invests in a staggered set of zero-coupon Treasury bonds with maturities from 1 to 10 years. Each year, the maturing tenth of these bonds are reinvested in new 10-year bonds. The resulting duration is 5.5 years, hence to achieve the target asset duration of 4.3 years (see Table A.1), 21.8% of the portfolio is invested at the Fed funds rate. The portfolio is funded by borrowing 40% at the 1-year Treasury rate and 60% at the Fed funds rate for a target liabilities duration of 0.4 years. The net interest margin (NIM), interest income, and interest expense of the simulated portfolio are computed using standard bank accounting. The data are annual, from 1955 to 2015.

Panel A: Net interest margin (NIM)



Panel B: Interest income and expense

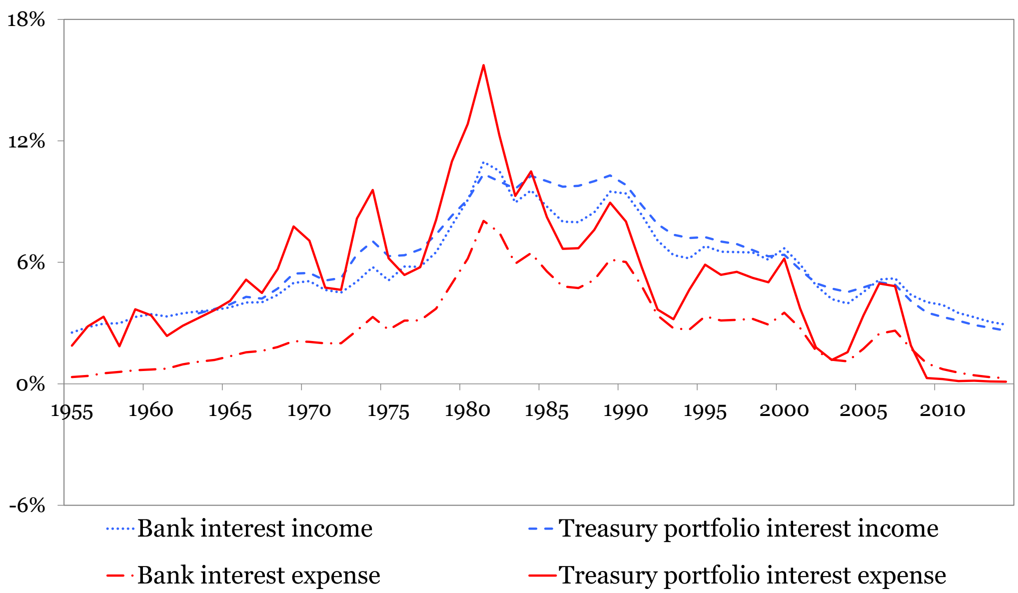
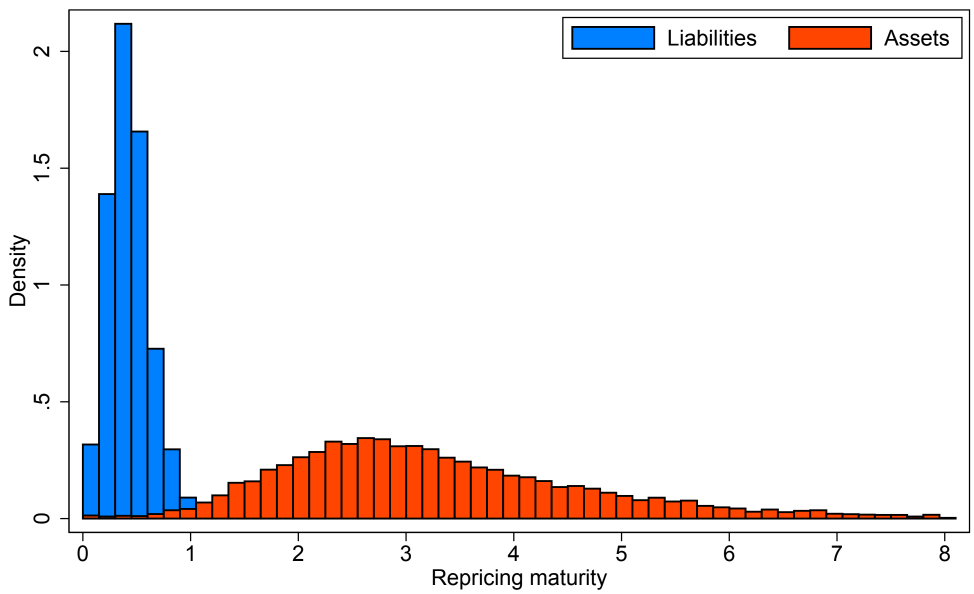


Figure A.2: **Estimated duration of bank assets and liabilities**

The figure plots the distribution of repricing maturity, a proxy for duration, of bank assets and liabilities. 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 is from 1997 to 2013.

All banks



Top 5%

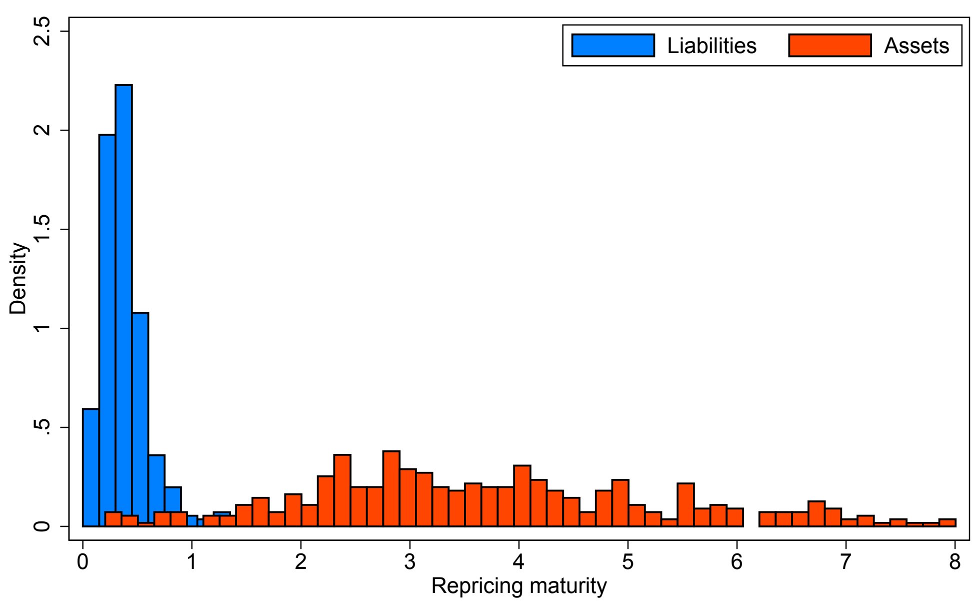
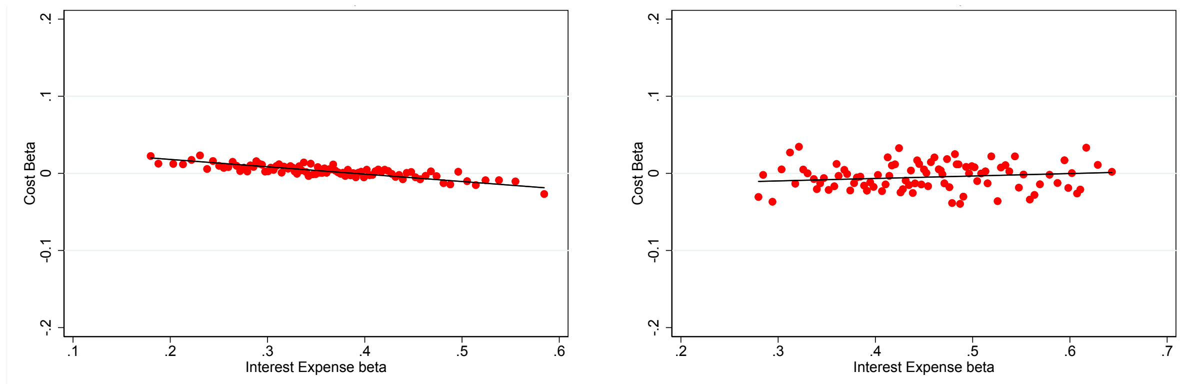


Figure A.3: **The interest rate sensitivity of operating costs and fee income**

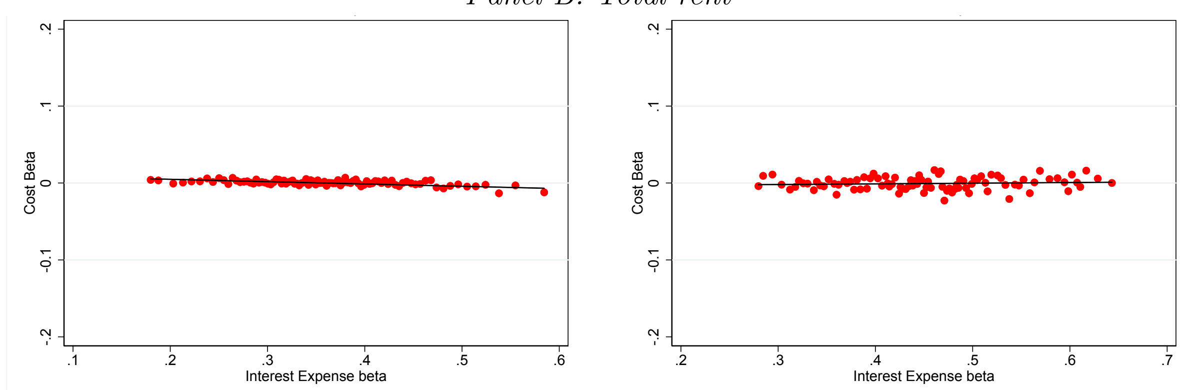
This figure shows bin scatter plots of bank operating costs and deposit fee income by expense betas. The betas and scatterplots are constructed the same was as in Figure 5. The left column is for all banks and the right column for the top five percent of banks. The top panel provides information on total salaries, the middle panel on total rent, and the bottom panel on deposit fee income.

All banks | Top 5%

Panel A: Total salaries



Panel B: Total rent



Panel C: Deposit fee income