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 over 1955–2013, 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 these liabilities 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. Furthermore, banks with lower interest expense sensitivity hold assets with substantially longer duration. We exploit cross-sectional variation in market power and show that it generates variation in expense sensitivity that is matched one-for-one by income sensitivity. 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, but it also exposes them to interest rate risk. An unexpected rise in the short-term rate drives up interest expenses relative to income, compressing net interest margins and depleting bank capital. Interest rate risk is therefore viewed as fundamental to the business of banking, and it underlies discussion of how monetary policy impacts the health of the banking system.[1]

We show that, in stark contrast to this standard view, banks have little exposure to interest rates changes. Panel A of Figure 1 shows that, from 1955 to 2013, the net interest margin (NIM) of the aggregate banking sector remained in a narrow band between 2.2% and 3.7% even as the short-term interest rate (represented here by the Fed funds rate) fluctuated widely and persistently. Moreover, movements in NIM within this narrow band have been very slow and gradual: yearly NIM changes have a standard deviation of just 0.13% and virtually no correlation with the Fed funds rate. This lack of sensitivity carries over directly to banks' bottom line: return on assets (ROA) displays virtually no relationship with interest rate fluctuations.

The explanation for this lack of sensitivity is *not* that banks are maturity-matched. Far from it. From 1997 to 2013, the years for which detailed data are available, the average repricing maturity (a proxy for duration) of aggregate bank assets was 4.3 years versus only 0.4 years for aggregate bank liabilities.[2] This duration mismatch of roughly 4 years is substantial, and is stable throughout the sample. It implies that a 100-bps positive shock to interest rates would lead to a running 100-bps increase in expenses relative to income for 4 years, and hence a 4 percentage point cumulative reduction in NIM. The lower NIM going forward would translate into a 4% decline in the value of assets relative to liabilities on

[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] Repricing maturity is the time until the interest rate on a contract resets, in contrast to maturity, which is the time until the contract terminates. An example illustrating the important difference is a floating rate bond whose interest rate resets every quarter even as the bond itself has long maturity. We use the terms repricing maturity and duration interchangeably in what follows, so long as it does not lead to any confusion.

impact. The interest rate shock need not happen at once, it can accumulate over time, and is in fact small by historical standards. Yet there has never been a comparable reduction in NIM over any period of time. This is fortunate because such a reduction in NIM would wipe out 40% of bank equity, as banks are levered ten to one.

In practice, a 100-bps shock to interest rates wipes out on average only 2.4% of bank equity. This is shown in Figure 2, which plots regression coefficients of industry portfolio returns on changes in the one-year Treasury rate around FOMC meetings.[3] The coefficient for commercial banks, -2.42, is very close to that for the overall market, -2.26. It is only the 23^{rd} most negative among the 49 industries. Banks are thus no more exposed to interest rate changes than the typical nonfinancial firm. While this may seem surprising given their large duration mismatch, it is entirely consistent with having cash flows that are insensitive to interest rate changes, as shown in Figure 1.

We show that banks have little interest rate exposure because the rates they pay on retail (core) deposits are insensitive to market interest rates despite having zero or near-zero maturity. Drechsler, Savov, and Schnabl (2017) show that this is due to market power in local deposit markets, which allows banks to keep rates low even as the Fed funds rate rises. As core deposits represent over 70% of bank liabilities, the sensitivity of banks' total interest expenses is substantially below one, its value for an institution with no market power, such as a money market fund. This is confirmed by Panel B of Figure 1, which breaks out the two components of aggregate NIM: the aggregate interest expense rate and the aggregate interest income rate. It shows that the interest expense rate is much smoother and flatter than the Fed funds rate, reflecting its low sensitivity.

The low sensitivity of interest expenses allows banks to hold substantial long-term assets without incurring losses if interest rates rise. Panel B of Figure 1 shows this too: like the interest expense rate, the interest income rate is smooth, so that NIM remains stable even as the Fed funds rate fluctuates widely. Market power on the deposit side thus equalizes the

[3] 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 actions). 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 as in English, den Heuvel, and Zakrajsek (2012).

interest-rate sensitivities of banks' income and expenses, despite the large duration mismatch between their assets and liabilities.

We argue that banks not only can but *must* hold substantial long-term assets. This is because of the risk of a *decline* in interest rates which, given banks' insensitive expense rate, would sharply compress NIM if assets were primarily short-term. This would lead banks to incur losses because of the substantial fixed costs (salaries, branches, marketing) associated with operating a deposit franchise and obtaining market power. These costs are reflected in the 2% gap between the average NIM and ROA. To hedge against an unexpected drop in rates, banks must hold sufficient long-term assets.

We build a simple model that captures these ideas. In the model, a bank invests so as to maximize expected profits while avoiding bankruptcy. To obtain deposits, the bank must pay fixed operating costs (branch, salary, advertising) which give it market power and thus allow it to pay a deposit rate equal to only a fraction of the short rate, as in Drechsler, Savov, and Schnabl (2017). On the asset side, markets are complete, so the bank can invest in any claim.

The model gives two insights. First, to avoid bankruptcy if the short rate is high, a bank must set the short-rate sensitivity of its income, which we call its income beta, to be at least as high as the short-rate sensitivity of its expenses, which we call its expense beta. The bank can achieve this by holding a sufficiently high share of short-term assets. Yet since market power drives the expense beta far below one, the required short-term share is much lower than suggested by deposits' short maturity. In contrast, without market power the bank would have an expense beta of one, which would require it to hold a short-term asset share of one, in line with standard concerns that maturity mismatch creates interest rate risk. Second, since the bank's operating costs do not depend on the short rate, its income stream must be insensitive enough to cover these costs, and avoid bankruptcy, if the short rate is low. Hence, the bank needs to hold a sufficiently high share of *long-term* assets paying a fixed income stream. When the rents on deposits are zero (i.e. the present value of their interest savings equals the present value of their operating costs), the model predicts that the bank must equalize its income and expense betas.

We test the model on the cross-section of all U.S. commercial banks for the years 1984 to 2013 using quarterly data from the Call Reports. We estimate banks' expense betas by regressing the change in their interest expense rates on contemporaneous and lagged changes in the Fed funds rate. We then sum the coefficients to obtain estimates of the betas. We find that there is substantial heterogeneity in the distribution of expense betas, with significant mass at values ranging from less than 0.2 to more than 0.6. Hence, even across banks themselves there are large differences in the sensitivity of interest expenses.

We then analyze whether banks match the interest sensitivities of their expenses and incomes. We do so by constructing interest income betas analogously to the expense betas. We find that the expense and income betas line up well, revealing careful matching. The slope of the relationship is 0.768 for the sample of all banks, and 0.878 for the largest 5% of banks. These numbers are close to one, leaving banks' net interest margin largely unexposed. Indeed, when we look at banks' bottom line profitability, ROA, its sensitivity to Fed funds rate changes is close to zero and its relationship with expense betas is flat. Banks are thus able to engage in significant maturity transformation without exposing themselves to significant interest rate risk.

This conclusion is confirmed when we look at stock price reactions to interest rate changes. Following the same methodology as in Figure 2, we calculate an "FOMC beta" for each publicly traded commercial bank. As in Figure 2, the average bank's FOMC beta is similar to that of the overall market. Moreover, FOMC betas are flat as a function of both interest expense and income betas. The latter result in particular shows that the amount of long-term assets on a bank's balance sheet is unrelated to its interest rate exposure. This is consistent with a high degree of matching coming from the liabilities side.

We use panel regressions to produce precise estimates of the expense and income matching. We employ a two-stage procedure. In the first stage, we again regress interest expense rate changes on contemporaneous and lagged Fed funds rate changes. In the second stage, we regress interest income rate changes on the fitted value from the first stage. This regression asks if banks whose interest expense rate goes up more when the Fed funds rate rises also see their interest income rate go up more. We find that the answer is yes: the matching coefficient is 0.765 for all banks and 1.114 for the top 5%, indicating near-perfect one-to-one matching among the bulk of the banking sector by assets. In all cases the direct effect of Fed funds rate changes holding interest expense rate changes fixed is close to zero, which implies that a bank with zero interest expense rate sensitivity is also predicted to have zero interest income rate sensitivity. At the other extreme, a bank whose interest expense rate rises one-for-one with the Fed funds rate (similar to a money market fund) is predicted to have an interest income rate that also rises one-for-one, i.e. it would have to hold only short-term assets and therefore not engage in any maturity transformation.

A natural way for banks to match income to expense betas is through their holdings of long-duration assets. We examine this relationship directly using the information in the Call Reports on the repricing maturity of various banks long-term assets (loans and securities), which is available since 1997. We find a strong cross-sectional relationship between banks' average asset repricing maturity and their expense betas. The regression coefficient is -3.662 years, which is highly significant and similar in magnitude to the average repricing maturity of bank assets. The coefficient is robust to a number of control variables such banks' wholesale funding ratio, equity ratio, and size. This shows that alternative mechanisms, such as liquidity risk and capitalization, are unlikely to explain our results.

We provide direct evidence for the market power mechanism underlying our model by exploiting several sources of variation in market power. The first is market concentration (using a Herfindahl index), which Drechsler, Savov, and Schnabl (2017) show is related to the sensitivity of deposit rates to interest rate changes. We incorporate this measure into our two-stage panel regression framework by using it to parameterize the sensitivity of banks' interest expense rates to changes in the Fed funds rate. We find that banks that operate in concentrated markets have lower interest expense rate sensitivity and that this is matched by lower interest income sensitivity. The second-stage coefficient is again close to one. This shows that variation in market power is associated with interest rate sensitivity matching, as implied by our model.

As an alternative source of variation in market power, we estimate the sensitivities of the rates banks offer on different retail deposit products (interest checking, savings, and small time deposits) at branches located in different markets using data from the provider Ratewatch. We purposely choose products that are well below the deposit insurance limit, which ensures that we are not picking up variation that is directly induced by run risk (or liquidity risk more broadly). We show that these retail deposit betas are associated with significant variation in banks' overall interest expense rate sensitivities, and that this variation is matched one-for-one by variation in interest income sensitivities. This is consistent with the model where retail deposits are the source of banks' market power and low interest expense sensitivity, which is in turn matched by holding long-term assets.

We take this approach one step further by adding bank-time fixed effects in the estimation of the local retail deposit betas. We are thus comparing the rates offered in different markets by branches belonging to the same bank. This purges the betas of bank-level characteristics such as liquidity risk and gives us a cleaner measure of market power in retail deposit markets. We then re-estimate our two-stage panel regressions using the purged retail deposit betas. The coefficients are very similar to our main results and are again very close to one.

We also provide evidence that banks with low interest expense betas have more extensive branch networks, a costly investment in deposit acquisition. We proxy for the extensiveness of a bank's branch network with its log ratio of deposits per branch. A lower value implies a greater investment in deposit acquisition per deposit dollar. Consistent with the model, a lower log deposits-per-branch ratio, which indicates greater cost, is associated with significantly lower interest expense betas. The relationship is especially strong for the interest expense betas of retail deposits such as savings deposits.

The final part of our analysis looks more closely at the asset side of bank balance sheets. We focus specifically on banks' shares of securities versus loans, the two main categories of bank assets. On average, loans have a relatively low repricing maturity of 2.6 years. Consistent with this, the share of a bank's total assets in loans is strongly increasing in its expense beta. Hence, banks with interest sensitive liabilities hold a significantly larger share of their assets in loans. As loans are the most *illiquid* type of asset, this shows that high-expense beta banks do not choose shorter maturities out of a need for greater liquidity. Securities, on the other hand, have a high average repricing maturity of 5.6 years (many are mortgage-related), and we find that their share is strongly decreasing in banks' interest expense betas. That is, banks with low interest sensitivity hold more securities, which is a primary means of obtaining duration. All of these results are unchanged when we look at the largest 5% of banks.

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.

A final possibility we consider is that the sensitivity matching we observe is somehow the product of market segmentation. For instance, it could be that banks that raise deposits in markets with a lot of market power tend to have more long-term lending opportunities. While it is difficult to imagine that such a correlation could explain the one-to-one beta matching we find in both aggregate and cross-sectional data, we are able to test this possibility directly. To do so, we check if banks match the interest income sensitivities of their securities holdings, and in particular their Treasury and MBS holdings, to their expense betas. Since these securities are bought and sold in open markets, they are immune to the market segmentation concern. We once again find a close match, implying that banks intentionally match their 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 shows our results on market power; Section VII looks at the asset side of bank balance sheets; and Section VIII concludes.

II Related literature

Banks issue short-term deposits and make long-term loans. This dual nature underlies banking theory. While deposit-centric theories emphasize liquidity provision (Diamond and Dybvig 1983, Gorton and Pennacchi 1990), loan-centric ones emphasize screening and monitoring (Leland and Pyle 1977, Diamond 1984). The question arises, why perform both functions under one roof, especially given the risks inherent in liquidity and maturity transformation. Liquidity transformation is addressed by Calomiris and Kahn (1991), Diamond and Rajan (2001), Kashyap, Rajan, and Stein (2002), and Hanson, Shleifer, Stein, and Vishny (2015).

Liquidity risk is further reduced by deposit insurance.[4]

Our contribution is to offer an explanation for why banks engage simultaneously in maturity transformation and deposit taking. We argue that market power in deposit markets and the costs associated with maintaining it lower the interest rate sensitivity of banks' expenditures so they resemble fixed-rate liabilities. Under these conditions, maturity mismatch actually *reduces* interest rate risk. Consistent with this view, we find that banks set their maturity mismatch so that they face minimal interest rate risk. This has allowed the banking sector to maintain near-constant profitability in the face of deep cycles and prolonged trends in interest rates over the past sixty years.

Other explanations for why banks engage in maturity transformation 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 models in this tradition, maturity transformation varies with the size of the term premium and banks' effective risk aversion (He and Krishnamurthy 2013, Brunnermeier and Sannikov 2014, Drechsler, Savov, and Schnabl 2015). In Di Tella and Kurlat (2017), as in our paper, deposit rates are relatively insensitive to changes in interest rates (due to capital constraints rather than market power). This makes banks less averse to interest rate risk than other agents and induces them to engage in maturity transformation in order to earn the term premium.[5]

In contrast to this literature, instead of a risk-*taking* explanation, we provide a risk-*management* explanation for why banks engage in maturity transformation, one that does not require the presence of a term premium.[6] While both risk-taking and risk-management are consistent with maturity transformation in general, the risk-management explanation makes the strong prediction that we should observe one-to-one matching between between banks' interest income and interest expense.

This is important because it implies that banks are relatively insulated from the balance

[4] Gatev and Strahan (2006) show that thanks to deposit insurance banks actually experience inflows of deposits in times of stress, which in turn allows them to provide more liquidity to their borrowers.

[5] Recent estimates indicate that the Treasury term premium has declined and indeed turned negative in recent years (see https://www.newyorkfed.org/research/data_indicators/term_premia.html). At the same time, we find that the average bank's maturity mismatch has increased from about 3 years in 2008 to 4.7 years in 2013.

[6] See Froot, Scharfstein, and Stein (1994) for a general framework for risk management and Nagel and Purnanandam (2015) for a structural model.

sheet channel of monetary policy (Bernanke and Gertler 1995), which works through the influence of interest rate changes on net worth. It also addresses concerns about whether maturity transformation leads to financial instability (Kohn 2010). The risk of such instability is sometimes invoked as an argument in favor of narrow banking (the idea that banks should hold only short-term safe instruments, see Pennacchi 2012). Our analysis suggests that narrow banking would increase, rather than decrease, commercial banks' exposure to interest rate risk.

Brunnermeier and Koby (2016) argue that banks might become unstable when the short rate is sufficiently negative because they cannot pass it through to their depositors. They call the rate at which this happens the reversal rate and explore its implications for the optimal conduct of monetary policy. Within our framework, a negative short rate would also put banks' profit margins under pressure once their long-term assets roll off. Interestingly, our data show that banks in the U.S. lengthened the duration of their balance sheets during the zero-lower-bound period, which has limited the compression of their net interest margins.

The empirical literature provides estimates of banks' exposure to interest rate risk. In a sample of fifteen banks, Flannery (1981) finds that bank profits have a surprisingly low exposure to interest rate changes and frames this as a puzzle. Other studies look at the reaction of banks' stock prices to interest rate changes, typically finding a negative reaction (Flannery and James 1984a, English, den Heuvel, and Zakrajsek 2012). English, den Heuvel, and Zakrajsek (2012) find that a 1% level shock to the yield curve causes bank stocks to drop by between 8 and 10%. This is only modestly higher than the estimates for the entire stock market in Bernanke and Kuttner (2005) (see, in particular, Table III for a comparable sample). As we discussed in the Introduction, given the average maturity mismatch and high leverage, one would expect bank stocks to instead decline by 40%.

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, derivative use is limited and may actually increase banks' maturity mismatch. This is consistent with our explanation where banks have little interest rate risk to hedge.

As Drechsler, Savov, and Schnabl (2017) show, banks with insensitive deposit rates see greater deposit outflows when interest rate go up (this is consistent with their increased market power). This causes their balance sheets to contract even though profitability remains the same. Combined with the sensitivity-matching result in this paper, this can shed light on the results in Gomez, Landier, Sraer, and Thesmar (2016) that banks with a bigger income gap (a measure of maturity mismatch) contract their lending by more following an interest rate increase. Moreover, our results suggest that banks should become less willing to hold long-maturity assets as their deposits flow out. This can shed light on the finding in Haddad and Sraer (2015) that the income gap negatively predicts bond returns.

A canonical example of interest rate risk in the financial sector comes from the Savings and Loans (S&L) crisis of the 1980s. A drastic rise in interest rates inflicted significant losses on these institutions, which were then further exacerbated by excessive credit risk-taking (White 1991). We draw two lessons from this episode. First, it is remarkable that unlike the S&L sector, the commercial banking sector saw no decline in net interest margins during this period, despite the fact that the rise in interest rates was without historical parallel. Second, as White (1991) shows, 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 large shock on their funding costs. Thus, when it comes to banks' interest rate risk exposure, the S&L crisis is in many ways the exception that proves the rule.

The deposit-pricing literature has documented the low sensitivity of deposit rates to market rates (Hannan and Berger 1991, Neumark and Sharpe 1992, Driscoll and Judson 2013, Yankov 2014, Drechsler, Savov, and Schnabl 2017), which plays an important role in our paper. This literature has recently been extended to a wider set of instruments (Nagel 2016, Duffie and Krishnamurthy 2016).

A subset of the deposit-pricing literature estimates the effective duration of deposits using stock price data (Flannery and James 1984b) or aggregate deposit rates (Hutchison and Pennacchi 1996) and finds that deposits have an effective duration that is significantly higher than their contractual maturity.[7] Our paper connects the interest rate sensitivities of

[7]This literature focuses on the contribution of deposit rents to bank valuations. A recent paper in this

the two sides of bank balance sheets and shows that they match so that banks are effectively insulated from interest rate risk.

The deposits literature has also examined the relationship between deposit financing and asset holdings. Hanson, Shleifer, Stein, and Vishny (2015) show that commercial banks are better suited to holding fixed-rate assets than shadow banks because bank deposit funding is more stable than shadow bank funding. Berlin and Mester (1999) argue that deposit financing allow banks to smooth aggregate credit risk in lending. Kirti (2017) argues that banks with higher deposit rate pass-through are more aggressive in supplying floating-rate loans. Our paper focuses on the role of deposits in hedging interest rate risk and thus enabling banks to engage in maturity transformation.

III Model

We model the investment problem of a bank. Time is discrete, the short rate is given by the stochastic process f_t, 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 the present value of its future profits, subject to the requirement that it remain solvent so that 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 obtain and service deposit customers. Importantly, the deposit franchise gives the bank market power over deposits, which allows it to pay depositors a deposit rate of only

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

where $0 \leq \beta^{Exp} < 1$. Drechsler, Savov, and Schnabl (2017) construct a model that micro-founds this deposit rate as the solution to the optimization problem of a bank with market

area is Egan, Lewellen, and Sunderam (2016), which finds that deposits are the main driver of bank value.

power in the deposit market. A bank with high market power has a low value of β^{Exp}, while a bank that has little 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-maturity 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 investors, banks use this stochastic discount factor when valuing profits.

The bank therefore solves

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

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

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

where INC_t is the time and state contingent income stream produced by the bank's 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 be equal its current value of one dollar. Equation (4) is the solvency constraint: the bank's income in any time and state must exceed its interest expenses $\beta^{Exp} f_t$ and operating costs c.

Thus, the bank faces two solvency risks. The first is that its interest expenses rise with the short rate ($\beta^{Exp} \geq 0$), 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 concerns 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 concerns are focused on the liabilities' short duration, because this suggests a high sensitivity to the short rate. However, due to market power the bank's interest expense beta β^{Exp} may be far below one, in which case so can the fraction of its holdings that are invested in 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 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 only generates small interest savings, yet continues to incur the same level of operating costs. To hedge against this low-rate scenario, the bank must hold a sufficient fraction of its portfolio in long-term bonds.

These conditions pin down the bank's portfolio when the bank makes no rents, i.e., $V_0 = 0$, as is the case if there is free entry into the banking industry. We then obtain the following.

Proposition 1. *Under 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:

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

When there are no rents, the present value of the interest savings generated by the deposit franchise is equal to the present value of its operating costs.[8] The bank must therefore apply the 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 section by analyzing the cross section of banks.

Finally, we note that 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}

[8]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 free entry a lower expense beta β^{Exp} requires a higher operating cost c.

share of its assets in short-term bonds, and the remaining $1 - \beta^{Exp}$ share in long-term fixed rate bonds. We use this observation to provide additional empirical tests of our model.

IV Data

Bank data. The bank data is from 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.

Part of our analysis utilizes a proxy for duration, which we refer to as repricing maturity. The repricing maturity of an instrument is the time until its rate resets (in case of a floating-rate instrument) or the time until it matures (in case of a fixed-rate instrument). To calculate repricing maturity 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 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). We then calculate a weighted average of these midpoints using the amounts in each bin as weights.[9] We compute a bank's repricing maturity as the weighted average across all maturities and asset classes.[10]

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

[9]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.

[10]Banks do not report the repricing maturities of their remaining assets which are mostly short-term (mainly cash and Fed funds sold). Our results are robust to including these assets in our measure, where we assign them a repricing maturity of zero.

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.

The top panel in Figure 3 plots the repricing maturity of asset and liabilities for the sample of all banks. It is clear from the figure that there is a significant mismatch between assets and liabilities. Assets have an average repricing maturity of 3.349 years with a standard deviation of 1.587 years, while liabilities have an average repricing maturity of 0.441 years with a standard deviation of 0.213 years. The bottom panel of Figure 3 plots repricing maturity for the top 5% of banks by assets. We find that the maturity mismatch is even more pronounced for this group: assets and liabilities have average repricing maturity of 4.045 and 0.402 years, respectively.

We stress that repricing maturity is only a coarse proxy for duration. The available categories and time intervals are broad and allow for substantial variation within them, which we do not observe. Repricing maturity also does not do not take into account yields, intermittent payments, or prepayment risk, all of which influence duration. Nevertheless, repricing maturity gives us some idea of the amount of maturity transformation that banks are engaged in. It also helps us to validate our income and expense-based measures of interest rate sensitivity.

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 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. Ratewatch collects weekly branch-level data on deposit rates by product from January 1997 to December 2013. The data cover 54% of all U.S. branches as of 2013. We merge the Ratewatch data with the branch-level FDIC data using the FDIC branch identifier and from there to the bank-level Call Reports. The Ratewatch data report whether a branch actively sets its deposit rates or whether its rates are set by a parent branch. We limit the analysis to branches that actively set their rates to avoid duplicating observations. We use data on the three most commonly offered retail deposit products across all U.S. branches: money market deposit accounts with an account size of \$25,000, 12-month certificates of deposit (CDs) with an account size of \$10,000, and interest checking accounts with an account size of under \$2,500. These products are representative of savings deposits, small time deposits, and checking deposits, which are the three main types of retail deposits. Since their balances are well below the deposit insurance limit (\$100,000 for most of the sample), these are insured deposit accounts.

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 The interest rate risk exposure of banks

Our model predicts that banks should match the interest rate sensitivity of their assets and liabilities. In this section, we first explain how we measure this sensitivity using interest income and interest expense and then test whether the matching takes place.

V.A Measuring the interest rate sensitivity of liabilities

We measure the interest rate sensitivity of banks' liabilities 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:

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

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.[11] Our estimate of bank i's expense beta is the sum of the coefficients in (7), i.e. $\sum_{\tau=0}^{3} \beta_{i,\tau}$. To calculate an expense beta, we require a bank to have at least five years of data over our sample from 1984 to 2013. This yields 18,871 observations.

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 0.355, which means that interest expenses increase by 35.5 bps for each 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 0.438 bps. There is significant variation across banks with a standard deviation of 0.102.

The low average expense beta suggest that banks earn large spreads on their liabilities when interest rates rise. The average size of the banking sector from 1984 to 2013 is \$6.763 trillion, which implies an increase in annual bank revenues of $(1 - 0.436) \times \$6,763 = \$38$ billion for a 100 bps increase in the Fed funds rate. The revenue increase is permanent as long as the Fed funds rate remains at the same level. It is large compared to the banking sector's average annual net income of \$59.5 billion over the same period.

Table 1 presents a breakdown of bank characteristics by whether a bank's expense beta is above or below average. We compute the bank characteristics by averaging over time for each bank. The table shows that the difference in banks' expense betas is not explained by the repricing maturity of their liabilities, which is similar across the two groups (0.458 versus 0.415 years). The reason is that repricing maturity does not capture that banks raise the spreads on short-term liabilities when interest rates rise. This can instead be seen in the large difference in core deposit expense betas between the low- and high-expense beta banks (these are computed analogously to the overall expense betas). It can also be seen in the somewhat higher proportion of core deposits among low-expense beta banks (75.2% versus 71.4%).

[11] 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 flatten out. Our results are robust to including more lags.

V.B Income and expense beta matching

As we saw in the top panel of Figure 1, the banking sector as a whole has closely matched interest income and interest expenses over 1955 to 2013 even as the level of interest rates in the economy has varied widely. As we saw in the bottom panel of Figure 1, this has led to highly stable net interest margin and ROA. In this section, we show that this matching of sensitivities extends to the cross section. This indicates that interest rate risk is minimized at the level of the individual bank as implied by our model.

V.B.1 Cross-sectional analysis

To analyze matching, we compute interest income betas by running analogous regressions to (7) but with banks' interest income rate as the dependent variable. Interest income includes all interest earned on loans, securities, and other assets. The advantage of interest income betas is that we can compare them directly to the interest expense betas. Our model predicts that the two should be equal. This one-to-one matching provides us with a strong quantitative prediction that is unique to our theory.

Table 1 shows summary statistics for interest income betas and the bottom panel of Figure 4 plots their distribution. The average income beta is 0.372 with a standard deviation of 0.153. The estimate for the largest 5% of banks by assets is 0.436. It is clear from the two panels of Figure 4 that the distributions of expense and income betas are very similar with nearly identical means. Moreover, as Table 1 shows, income betas are significantly higher for high-expense beta banks than low-expense beta banks (0.308 versus 0.435). The levels of income and expense betas across the two groups also line up well, as they do across the all-bank versus top-5% categories. These simple moments of the data indicate tight matching between income and expense sensitivities to interest rate changes.

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 where we group banks into 100 bins by expense beta and plot the average 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. Above each plot is the coefficient and R^2 from the corresponding cross-sectional regression (the regression line is depicted in black).

The plots show a strong alignment of banks' income and expense sensitivities to interest rate changes. Among all banks, the slope coefficient is 0.768, while among the top 5% of banks it is 0.878. These numbers are close to one, as predicted (in the next section we use panel regressions to estimate them more precisely). The R^2 coefficients are high, 26.8% among all banks and 33.8% among large ones (the relationship looks noisier for large banks simply because each bin has 95% less observations). Expense betas thus explain a large fraction of the variation of interest rate sensitivities across banks.

The bottom two panels of Figure 5 show that the strong matching effectively insulates bank's profitability from interest rate changes. Our measure of profitability is return on assets (ROA), which is equal to banks' net interest margin (interest income minus interest expense) minus net non-interest expenses (non-interest expenses such as salaries and rent minus non-interest income such as fees). We estimate banks' ROA betas in the same way as their expense and income betas (see (7)).

As the bottom panels of Figure 5 show, ROA is essentially insensitive to interest rate changes both among all banks and among large ones. The relationship with expense beta among all banks is flat, despite the fact that the matching coefficient for this group is a bit below one. This indicates that non-interest expenses provide somewhat of an offset so that profitability is ultimately unaffected. Among the top 5% of banks, ROA betas are slightly lower for high-expense beta banks (the coefficient is -0.191). However, the relationship is noisy and as we see in the panel regressions below, a more precise estimate shows that it is very close to zero. This shows that the matching of interest expense and income betas insulates banks' profitability from interest rate changes.

We can go a step further and look at equity returns, which reflect changes in the present value of future ROA. We obtain a list of publicly listed bank holding companies that allows us to map bank holding company regulatory data to CRSP stock returns.[12] We use the regulatory data to compute interest expense and income betas. We use the stock return data to compute FOMC betas as we did for Figure 2. We regress each bank's return on the change in the one-year Treasury rate over a two-day window around scheduled FOMC

[12]We thank Anna Kovner for providing this list.

announcements from 1994 to 2008. We then merge the FOMC betas with the interest expense and income betas. The merged sample contains 790 bank holding companies. The average FOMC beta is -1.40, which is a bit smaller but otherwise similar to the industry-level FOMC beta in Figure 2.

Figure 6 shows a bin scatter plot of FOMC betas against interest expense and income betas. In both cases, the relationship is flat, echoing our results for ROA. The lack of a positive association with the income betas, in particular (if anything, the point estimate is negative), indicates that banks with more long-term assets are no more exposed to interest rate changes than other banks.[13] This result is puzzling under the view that maturity transformation exposes banks to interest rate risk. Rather, it is consistent with our framework where banks are able to avoid this risk even as they engage in maturity transformation by matching the interest rate sensitivities of their assets and liabilities.

V.B.2 Panel analysis

In this section we use panel regressions to produce more precise estimates of interest rate sensitivity matching. Panel regressions use all of the available variation in the data while cross-sectional regressions average some of it out. They also implicitly give more weight to banks with more observations whose exposures are estimated more precisely. Another advantage is that we can include time and bank fixed effects to control for common and bank-specific 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 rates using the following OLS regression:

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

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

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

the lag coefficients, here we utilize them fully to construct the fitted value $\Delta \widehat{IntExp}_{i,t}$ (this is another reason the panel regressions improve precision). This fitted value captures the predicted change in a bank'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 also 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 $t+1$, λ_i and θ_t are bank and time fixed effects, and $\Delta \widehat{IntExp}_{i,t}$ is the predicted change in the interest expense rate from the first stage. The coefficient of interest is δ, which captures the matching of income and expense rate changes. In some specifications, we replace 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 resulting estimate $\sum_{\tau=0}^{3} \gamma_\tau$ then gives the predicted interest income sensitivity of a bank with zero interest expense sensitivity (the analog to the intercept in the cross-sectional regression). We double-cluster standard errors at the bank and quarter level.

Table 2 presents the results. Columns (1) and (2) report the results for the full sample of banks, first with the Fed funds rate changes as controls and then with time fixed effects. We find coefficients of 0.765 and 0.766, respectively, which are again close to one.[14] The stand-alone coefficient on Fed funds rate changes is small at 0.093, indicating that a bank with zero interest expense sensitivity is predicted to have a very low interest income sensitivity. The high similarity between columns (1) and (2) indicates that the matching is not driven by some type of common time series variation.

Columns (3) to (8) report results for larger banks using the top 10%, top 5% and top 1% sub-samples. Here the coefficients are almost exactly equal to one, ranging from 1.012 for the top 10% of banks to 1.114 for the top 5%. None of the estimates are more than one and a half standard errors away from one, hence we cannot reject the strong hypothesis of

[14] A coefficient of 0.765 implies that the sensitivity of banks' net interest margin is $(0.765 - 1) = -0.235$. Hence, by construction we find a coefficient of -0.235 if we estimate this regression using the change in net interest margin as the outcome variable in equation (9).

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 top-1% of banks. The stand-alone coefficient on Fed funds rate changes is small and statistically insignificant and the coefficients are almost unchanged when we replace it with time fixed effects (columns (4), (6), and (8)). This again shows that a bank with insensitive interest expenses is predicted to hold long-term assets while a bank whose interest expense rate moves one-for-one with the Fed funds rate is predicted to hold only short-term assets.

Table 3 presents results for the sensitivity of banks' ROA. We use the same two-stage procedure except we replace the change in the interest income rate 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 subsets of banks. They are unchanged whether we control for the Fed funds rate (columns (1), (3), (5), and (7)) or include time fixed effects (columns (2), (4), (6), (8)). We note that these results imply that non-interest income and expenses are insensitive to interest rate changes, consistent with interpreting banks' operating costs as recurring fixed costs.[15]

Taken together, Tables 2 and 3 provide strong evidence that banks match the interest rate sensitivities of their assets and liabilities. This is despite the fact that each side of the balance sheet is itself highly sensitive with a large amount of cross-sectional variation (see Figure 4). The end result of this tight matching is that banks' profitability is almost perfectly insulated from interest rate changes. Banks are thus able to engage in substantial maturity transformation without bearing the interest rate risk it would normally entail.

V.C Time-series analysis

Panel A of Figure 7 provides evidence on matching in the time series. We sort banks into 20 bins by expense beta and plot the average interest income and interest expenses rates for the top and bottom bin from 1984 to 2013. For comparison, we also plot the Fed funds rate, which has trended downward over this period while also exhibiting wide variation over the

[15]We further show in the robustness section that the main categories of operating costs are insensitive to interest rate changes.

business cycle.

We see that the interest expense rates of high-expense beta banks follow the Fed funds rate quite closely both in the cycle and in the trend. Importantly, the interest income rates of these banks exhibit the same feature. By contrast, low-expense beta banks have both insensitive interest expense and interest income rates. The synchronized movements of the income and expense series of these two groups of banks are particularly clear in times when the Fed funds rate is high, such as the late 1980s, mid-to-late 1990s, and mid-2000s.

This again shows that there is tight matching of interest income and expense rates, both over time and across banks. Relative to the cross-sectional and panel analysis, the time series evidence does not impose parametric restrictions on how income and expenses vary with the Fed funds rate. While banks are sorted according to expense betas, the plot shows the actual dynamics of their interest income and expense rates.

The plot also shows that the average interest expenses of low-expense beta banks is below that of high-expense beta banks. This is consistent with the model where low-beta banks have more market power and offer lower deposit rates. We also see that low-expense beta banks have lower interest income than high-expense beta banks. This is driven by the fact that low-expense beta banks hold relatively fewer loans and more securities than high-expense beta banks (for more detail see the discussion below). Since banks charge a spread to cover expected losses on loans (as well as other costs such as monitoring), this difference in asset composition can explain the observed difference in interest income rates.

Panel B of Figure 7 plots the net interest margin and ROA of high- and low-expense beta banks over the same time period. Both quantities are remarkably stable for both groups and effectively uncorrelated with the Fed funds rate. Consistent with the model, the ROA of high- and low-expense beta banks is about the same.[16]

[16]There is a dip in ROA around the 2008 financial crisis. The dip comes a bit earlier for low-expense beta banks. This is likely driven by losses on their greater holdings of mortgage-related assets. These losses occurred sooner than those on other assets because the housing bust preceded the broader recession.

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 Tables 2 and 3 indicate that this is indeed largely the case. We provide direct evidence for this here by analyzing the interest rate sensitivity of the main components of banks' non-interest expenses and income.

Banks' operating expenses are substantial: 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 (9).

The results are presented as bin scatter plots in Figure A.1, and are constructed in the same manner as Figure 5. The top panel shows that the interest rate 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 insensitive to changes in interest rates, consistent with the model.

Interest rate derivatives. Banks can use interest rate derivatives to hedge the interest rate exposure of their assets. Of course, in doing so they would be paying the term premium and thereby foregoing the excess return earned for engaging in maturity transformation. Prior studies have found that only a small fraction of banks use interest rate derivatives (Purnanandam 2007). Information on the notional values of derivatives held for non-trading (e.g., hedging) purposes is available in the call reports. However, the direction and maturity of the derivatives contracts are not available, making it impossible to precisely calculate exposures. We therefore simply rerun our main tests separately for banks that do and do not use interest rate derivatives.

The derivatives data is available since 1995. Consistent with prior studies, the overwhelming majority of banks (92.9% in our sample) have zero exposure to derivatives. Larger banks are more likely to use interest rate derivatives, yet even among the top 10%, 61.6% report zero exposure.

Appendix Table A.1 presents the results. Columns 1 and 2 include all banks with non-missing derivatives exposure in the post-1995 sample. As expected, the matching coefficients are close to one as in Table 2. Columns 3 and 4 show nearly identical coefficients for banks with zero derivatives exposure. 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 (indicating that these banks hold slightly too few long-term assets) can potentially explain the otherwise puzzling finding in Begenau, Piazzesi, and Schneider (2015) that banks appear to use derivatives to actually increase the interest rate exposure of their assets.

VI The role of market power

The aggregate and cross-sectional results we have seen so far show that banks match the interest rate sensitivities of their assets and liabilities. In this section we look into the mechanism behind these results. As in the model, we argue that market power in retail deposit markets is a key driver of the interest rate sensitivity of banks' liabilities. Banks with a lot of market power are able to keep their deposit rates low even as the Fed funds rate rises. Consistent with this view, we show that variation in market power generates variation in interest expense betas and that this variation is in turn matched by variation in interest income betas.

VI.A Empirical strategy

Shedding light on the mechanism behind our matching result allows us to assess the plausibility of alternative explanations. The main alternative explanation is that instead of interest rate risk, banks are trying to hedge liquidity risk. The argument is as follows. Wholesale funding has a higher interest rate sensitivity than core deposits, hence banks that rely on wholesale funding are likely to have higher interest expense betas. At the same time, wholesale funding is more runnable (or at least less stable) than core deposits, hence banks that rely on wholesale funding are likely to face more liquidity risk. One way to hedge liquidity risk is to hold a buffer of liquid assets, and if we add the assumption that short-term liquid assets are particularly useful to hold as a buffer, then banks that rely on wholesale funding will have both high interest expense betas and high interest income betas.

The liquidity risk explanation does not produce a one-to-one match between interest income and expense betas. The matching would instead be proportional to the size of the liquidity buffer (see, e.g., Drechsler, Savov, and Schnabl (2015)). It therefore cannot fully account for our main result. Nevertheless, given its importance in the literature it could be a significant contributing factor and we consider the robustness of our results to this alternative hypothesis.

We separate the market power mechanism from the liquidity risk mechanism by exploiting different sources of variation in market power that are progressively less likely to be correlated with liquidity risk. We use each source of variation within the same two-stage empirical framework we used in the previous section (see equations (8) and (9)). Specifically, we run

$$\Delta IntExp_{i,t} = \alpha_i + \eta_t + \sum_{\tau=0}^{3} \left(\beta_\tau^0 + \beta_\tau \times MP_{i,t}\right) \Delta FedFunds_{t-\tau} + \epsilon_{i,t} \tag{10}$$

$$\Delta IntInc_{i,t} = \lambda_i + \theta_t + \delta \Delta \widehat{IntExp}_{i,t} + \varepsilon_{i,t}. \tag{11}$$

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 instead of allowing each bank to have its own set of loadings on the Fed funds rate changes in the first stage, we now parameterize these loadings as functions of a market power proxy $MP_{i,t}$. Since we are interested in the relationship between market power and interest expense sensitivities, we also report statistics from the first stage regression. As before, all standard errors are double-clustered by bank and quarter.

VI.B Market concentration

Our first market power proxy is market concentration. To construct it, we use the FDIC data on deposits at the branch level to calculate a Herfindahl (HHI) index for each zip code with at least one bank branch. Specifically, we calculate each bank's share of the total number of branches in a zip code and sum the squared shares to calculate the zip-code HHI. We then create a bank-level HHI by averaging the zip-code HHIs of all of a bank's branches. The resulting average bank-HHI is 0.408 and its standard deviation is 0.280, indicating substantial variation. As an alternative measure, we also compute each bank's average share of the branches in each zip code where it operates. This measure has an average of 0.419 and a standard deviation of 0.269.

Figure 8 shows that there is a negative relationship between interest expense betas and market concentration. From the left panel, banks operating in zip codes with zero concentration have an average interest expense beta of 0.39 while those operating in one-bank-only zip codes have an average interest expense beta of 0.29. Similarly, the right panel of Figure 8 shows a similar negative relationship between interest expense betas and banks' average market share. Thus, higher market concentration is associated with a lower interest rate sensitivity on the liabilities side.

Table 4 presents the results of our two-stage estimation. The first two rows show that market concentration, measured either as HHI or bank market share, is significantly negatively related to the sensitivity of banks' interest expenses to Fed funds rate changes. In particular, the first-stage coefficient on the interaction between market concentration and Fed funds rate changes is between -0.084 and -0.103, which is similar to the slope of the cross-sectional regression line in Figure 8.

The bottom part of Table 4 shows that the variation in interest expense rates induced by market concentration is matched by variation in interest income rates. The second-stage coefficients are close to one and stable across specifications. They range from 1.214 to 1.265 and are never more than one and a half standard deviations away from one. After controlling for interest expense rates, the direct effect of Fed funds rate changes on interest income rates is close to zero and statistically insignificant, again indicating that a bank with zero interest expense sensitivity is predicted to have zero interest income sensitivity. These results are consistent with the market power mechanism behind our model.

VI.C Retail deposit betas

Although we have shown that market concentration is associated with interest rate sensitivity matching, it remains possible that banks that operate in concentrated markets face less liquidity risk. We address this challenge by focusing on variation in market power that is specifically related to insured, retail deposits, and hence less likely to be picking up liquidity risk.

We obtain such variation using the Ratewatch data which reports the rates offered on new accounts of different deposit products at branches throughout the U.S.. Specifically, using all branches in a given metropolitan statistical area (MSA), we estimate an MSA-level deposit rate beta by regressing deposit rates on Fed funds rates:

$$DepRate_{b,i,m,t} = \alpha_b + \gamma_i + \delta_m + \eta_t + \sum_{m=1}^{M} \beta_m \times FedFunds_t + \varepsilon_{b,i,m,t}, \tag{12}$$

where $DepRate_{b,i,m,t}$ is the deposit rate of branch b of bank i in MSA m on date t. This procedure gives us the MSA-level coefficients β_m, which capture the sensitivities of local deposit rates to the Fed funds rate. We run (12) separately for the three most common deposit products in our data: interest checking with size less than \$2,500, money market deposit accounts with size \$25,000, and 12-month CDs with size \$10,000. These products are representative of the three main types of core deposits, checking, savings, and small time deposits. We note that the account sizes are far below the insurance limits so that the variation we pick up in their rates is unlikely to directly reflect liquidity risk.

Once we estimate the MSA-level betas, we construct their bank-level counterparts by averaging them across all of a bank's branches (using branch deposits as weights) and then averaging again across the three products. We use this bank-level average retail deposit beta as our market power proxy in (10)–(11). The identifying assumption is that geographic variation in retail deposit betas is uncorrelated with liquidity risk.

The first two columns of Table 5 presents the results. The first stage estimates show that retail deposit betas have a strong impact on banks' overall interest expense rate sensitivity to Fed funds rate changes. The coefficient is highly significant and varies between 0.433 and

0.455. These numbers are reasonable given that retail deposits make up a little more than half of banks' balance sheets.

The second stage examines the matching. As shown in column 1, the matching coefficients are high and highly significant. They vary from 1.372 to 1.402, which is somewhat larger than our benchmark estimates (the standard errors are also higher so again we cannot reject the hypothesis of one-to-one matching). The effect of Fed funds rate changes on the interest income rates of banks with zero predicted interest expense sensitivity is again zero. These results show that geographic variation in retail deposit betas induces variation in interest expense sensitivities that is matched on the asset side of banks' balance sheets. Since this variation in retail deposit betas is unlikely to reflect liquidity risk and reflects local market power, this result provides evidence in favor of the market power mechanism behind our model.

We can also push this approach one step further by exploiting only within-bank variation in retail deposit betas. We do so by including bank-time fixed effects in the retail deposit beta estimation equation (12). The resulting estimates are identified by comparing the deposit rates of branches of the same bank located in different areas. Since liquidity risk varies at the bank level and not the branch level, this further purges the retail deposit betas from any connection to liquidity risk.

The results are presented in columns (3) and (4) of Table 5. As the first-stage estimates show, the retail deposit betas estimated using within-bank estimation have a significant and economically sizable impact on banks' overall interest expense rate sensitivity (the coefficients vary between 0.209 and 0.225). This is despite the fact that they are constructed in a way that ignores all bank-level variation in deposit rates.

As the second-stage estimates in columns (3) and (4) show, the within-bank retail deposit betas still induce strong matching between interest expense and interest income rates. The second-stage coefficient varies from 1.175 to 1.191, which is once again very close to one. Based on these results, we conclude that variation in market power is a significant driver of our interest rate sensitivity matching results, as implied by our model.

VI.D The importance of an extensive branch network

Banks in our model gain market power by expending resources to acquire a depositor base with an inelastic demand for deposits. The kind of resources we have in mind go toward building up a strong brand and an extensive branch network. In this section, we use this intuition to further examine the mechanism behind our matching results.

To do so, we construct a simple measure of the extensiveness of a bank's branch network: the log ratio of deposits per branch (using the FDIC data). The idea is that a bank with a more extensive branch network will have fewer deposits at each branch but that this will help it reach a broader base of customers for whom the competitiveness of the bank's deposit rates is relatively less important. We therefore expect to see banks with fewer deposits per branch have lower interest expense betas.

The left panel of Figure 9 presents a bin scatter plot of interest expense betas against the log deposits-per-branch ratio. We see a strong increasing pattern. For instance, a bank with a ratio of 2.5, which comes out to $12 million per branch, has an average expense beta of about 0.3, while a bank with a ratio of 4.5 or $90 million per branch has an average expense beta of 0.38.

The right panel of Figure 9 presents a similar bin scatter plot but with banks' interest expense beta for savings deposits along the vertical axis. This savings deposit beta is computed in the same way as the overall interest expense beta but with the interest expense rate on savings deposits in place of the overall interest expense rate. The plot shows an even stronger relationship: a bank with a log deposits-per-branch ratio of 2.5 is predicted to have a savings deposit beta of 0.25 while a bank with a ratio of 4.5 is predicted to have a savings deposit beta of 0.42. This result supports the view that a more extensive branch network is particularly useful for attracting retail savings deposits with a low interest rate sensitivity.

VII Interest expense betas and banks' asset-side characteristics

In this section we show direct evidence that interest expense betas are associated with large variation in the duration of banks' assets.

VII.A Repricing maturity

Our model predicts that banks with low expense beta take on more duration in order to match the interest rate sensitivities of their assets and liabilities. In our main results, we look directly at the interest sensitivity of income. This allows us to test the strong quantitative prediction of one-to-one matching between the two sides of banks' balance sheets. In this section, we show that underlying this matching is wide variation in banks' asset duration. We do so using repricing maturity as a proxy (it becomes available starting in 1997).

The left panel in Figure 10 shows the relationship between repricing maturity and interest expense beta in the cross section of banks (repricing maturity is averaged for each bank over time).[17] The relationship is strongly downward sloping with a statistically significant coefficient of -3.662 and R^2 of 5.2%. This shows that banks with low interest expense betas hold significantly more long-term assets than banks with high interest expense betas. For instance, a bank with an expense beta of 0.1 has an average repricing maturity of 4.75 years while a bank with an expense beta of 0.5 has an average repricing maturity of just 3 years. A bank with expense beta of one is predicted to have a repricing maturity of just one year or so. Thus, a bank funded entirely with short-term wholesale instruments is predicted to engage in almost no maturity transformation, similar to a money market fund.

The right panel in Figure 10 looks at a related proxy for duration, banks' share of short-term assets (those with repricing maturity of less than a year). As expected, we see a strong positive relationship: banks with low expense betas have significantly less short-term assets than banks with high expense betas. The coefficient is 0.193 and the R^2 is 2.7%. Overall,

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

Figure 10 provides direct evidence that variation in interest expense betas is associated with large variation in the amount of maturity transformation banks engage in.

We provide a formal test of the strength of the relationship between expense betas and repricing maturity by running panel regressions of the form

$$RepricingMaturity_{i,t} = \alpha_t + \delta ExpenseBeta_i + \gamma X_{i,t} + \epsilon_{i,t}, \tag{13}$$

where $RepricingMaturity_{i,t}$ is the repricing maturity of bank i at time t, $ExpenseBeta_i$ 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 share of wholesale funding (large time and brokered deposits plus Fed funds purchased and repo funding), the equity ratio, and bank size. As before, we double-cluster standard errors at the bank and time level.

Panel A of Table 6 presents the regression results for the sample of all banks. From column 1, the univariate coefficient on the interest expense beta is -3.979, which is similar to the cross-sectional coefficient in Figure 10 and highly significant. The coefficient remains stable and actually increases slightly as we add in the control variables in columns (2) to (4). The wholesale funding ratio has a significant negative coefficient consistent with the interpretation that liquidity risk induces banks to hold more short-term assets. However, the coefficient is comparably small: holding expense beta fixed, a wholesale-funding ratio of one would only lower repricing maturity by about seven months. By contrast, having an interest expense beta of one while holding the wholesale funding ratio fixed would lowers repricing maturity by three years and eight months.

Column (5) of Panel A of Table 6 runs a horse race between the interest expense beta and all of the other controls. The coefficient on the interest expense beta is -4.77, which shows that the relationship between expense beta and repricing maturity is even stronger after controlling for some basic bank characteristics. In particular, we see that liquidity risk is unlikely to explain this relationship.

Panel B of Table 6 repeats this analysis for the largest 5% of banks. Even though this sample has only 259 banks and 16 years (and double-clustered standard errors), the relationship between interest expense betas and repricing maturity is strong and clear. This is not the case for the wholesale funding ratio which now has the opposite sign and is insignificant. The coefficient on the expense beta is somewhat larger than in the sample of all banks, rising to -6.136 in the specification with all the controls (column (5)). As this number applies to large banks, it suggests that the aggregate banking sector would not engage in any maturity transformation if its interest expenses repriced one-for-one with the short-term rate.

VII.B Securities share

We now look more closely how banks with low expense betas obtain duration. From Table 1, it is clear that the primary way of doing so in general is by holding a lot of securities (most of which are mortgage-related). Securities have an average repricing maturity of 5.6 years, while loans are as much as three years shorter. Given these large differences, and given our results thus far, we expect banks with low expense betas to hold a larger share of securities.

This prediction is particularly useful since the liquidity-risk view predicts the opposite relationship. Unlike loans, securities can be sold in the open market and are therefore much more liquid. If high-expense beta banks are primarily concerned about liquidity risk, they should be the ones holding more securities.

Table 7 presents the results of panel regressions similar to (13) but with banks' securities share as the dependent variable. In particular, we include the same sets of controls. Looking first at the sample of all banks in Panel A, we see a strong and significant negative relationship between interest expense beta and the securities 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 given that the average securities share in Table 1 is 0.246. Their sign is also inconsistent with the liquidity risk interpretation. Instead, they show that banks with low expense betas obtain duration by holding a large amount of securities.

Panel B of Table 7 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, with the exception of size, the control variables either lose their significance or see their signs flip. We conclude that there is a robust relationship between interest expense betas and banks' holdings of securities, which are a primary source of duration on bank balance sheets.[18]

VII.C Market segmentation

Our model and empirical analysis focus on the role of market power in reducing the interest rate sensitivity of banks' liabilities and on banks' active decision to match this low sensitivity by investing in long-term assets. However, another interpretation is that the matching is not active but the result of market segmentation. For instance, it could be that banks that operate in areas with a lot of market power tend to also have more long-term lending opportunities. Related, there is evidence that banks wield market power on the lending side as well as the deposits side (Scharfstein and Sunderam 2014). If these two types of market power are correlated, then banks with a lot of both will have low pass-through on both the income and expense sides of their balance sheets.

Two of our results so far are hard to reconcile with these market segmentation interpretations. First, while they can generate a correlation between expense and income betas, there do not necessarily predict the one-to-one matching we see both in the aggregate and in the cross section. The low pass-through interpretation in particular predicts a matching coefficient far less than one since it applies only to the flow of new loans. Second, in Section V we used within-bank variation in retail deposit betas as a proxy for market power in deposit markets. This variation is by construction uncorrelated with lending opportunities, which accrue at the bank-level. Nevertheless, we think market segmentation is an interesting alternative to our main explanation and we seek to explore it further.

We do so by looking separately at the interest rate sensitivities of loans and securities. Securities are by definition traded in an open market and hence not subject to market segmentation. Therefore, under the market segmentation interpretation, we should not see matching between interest expense beta and the interest income beta of securities. To implement this idea, we re-run our main matching test using the two-stage procedure in

[18] We note that 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.

equations (8)–(9), but with banks' securities interest income rate as the second-stage outcome variable in place of their overall interest income rate.

Table 8 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 0.593 and 0.579, respectively, and highly significant. We stress that in this setting a coefficient less than one is not puzzling because the prediction of one-to-one matching only applies to the balance sheet as a whole.

Columns (3) to (8) look at various sub-categories of securities. Since banks sometimes retain some of the securities they themselves originate, an argument can be made that market segmentation applies even to securities. This argument, however, cannot be made for Treasury securities and agency debt, which are originated at the federal level and highly liquid. Columns (3) and (4) show that there is matching even within this category. Columns (5) to (8) show the same for mortgage-backed (MBS) and other securities.

Table 9 repeats the analysis of Table 8 for the top 5% of banks. The results are qualitatively the same. The only difference is that the matching coefficients are 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 on securities income support the view that banks are actively matching interest rate exposures rather than passively having their sensitivities matched as a result of market segmentation.

VIII Conclusion

The conventional wisdom is that banks expose themselves to interest rate risk by borrowing short and lending long. We argue that the opposite is the case: banks *reduce* their interest rate risk through maturity transformation. They do so by matching the interest rate sensitivity of their assets and liabilities even while maintaining a large maturity mismatch. On the liabilities side, banks achieve a low sensitivity because of market power in deposit markets. On the asset side, banks achieve a low sensitivity by holding long-term assets. This sensitivity matching leads to stable net interest margins and profitability even as interest rate change and keeps deposits risk-free.

We document empirically that banks equalize the interest rate sensitivities of assets and liabilities in aggregate and in the cross-section of U.S. banks. Across a wide number of specifications, we find a matching coefficient nearly equal to one, as predicted by our framework. The result holds when we exploit variation in market power, including using within-bank variation in retail deposit pricing across branches. We also find direct evidence that banks with more market power hold assets with higher duration, particularly by holding more long-term securities.

Our results have important implications for monetary policy and financial stability. Monetary policy is often thought to impact banks through the interest rate exposure of their equity (the "balance sheet channel"). Our results suggest that this channel might be weaker than previously thought. Concerns about financial stability are often invoked when discussing the interest rate risk exposure of banks. They have led to calls for narrow banking, the idea that deposit-issuing banks should only hold short-term assets. Our results suggest that narrow banking would increase, rather than decrease, the interest rate exposure of banks and therefore inadvertently reduce financial stability.

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Table 1: **Summary statistics**

Summary statistics at the bank level. Interest expense betas are calculated by regressing the change in a bank's interest expense rate on the contemporaneous and three previous quarterly changes in the Fed funds rate. Interest income and ROA betas are calculated analogously. A bank must have at least 20 quarterly observations for its beta to be estimated and the betas are winsorized at the 5% level. The aggregate column is computed as a weighted average across all banks, using lagged assets as weights. The top 5% of banks are those that have a top-5% average rank over the sample in terms of assets. The sample is from 1984 to 2013.

	All banks		Top 5%	Low beta	High beta
	Mean	St.Dev.	Mean	Mean	Mean
Interest expense beta	0.355	0.102	0.438	0.274	0.436
Interest income beta	0.372	0.153	0.436	0.308	0.435
ROA beta	0.041	0.163	0.018	0.038	0.044
Log assets	4.331	1.343	7.686	4.153	4.740
Loans/Assets	0.580	0.131	0.627	0.561	0.601
Securities/Assets	0.246	0.130	0.200	0.279	0.235
Equity/Assets	0.099	0.039	0.078	0.105	0.094
Subordinated debt/Assets	0.001	0.002	0.003	0.000	0.001
Deposits/Assets	0.854	0.081	0.764	0.856	0.851
Core deposits/Assets	0.730	0.119	0.646	0.752	0.714
Transaction deposits/Assets	0.231	0.079	0.205	0.239	0.225
Savings deposits/Assets	0.208	0.087	0.239	0.210	0.209
Small time deposits/Assets	0.287	0.117	0.193	0.299	0.276
Large time deposits/Assets	0.122	0.078	0.114	0.102	0.135
Asset repricing maturity	3.349	1.587	4.045	3.564	3.106
Liabilities repricing maturity	0.441	0.213	0.402	0.458	0.415
Securities repricing maturity	5.615	2.893	6.805	5.608	5.598
Loans repricing maturity	2.618	1.696	3.409	2.832	2.328
Small time deposits repricing maturity	0.969	0.313	1.048	1.019	0.908
Large time deposits repricing maturity	0.878	0.356	0.915	0.930	0.811
Deposit beta	0.377	0.302	0.428	0.299	0.481
Core deposit beta	0.344	0.510	0.373	0.274	0.406
Transaction deposit beta	0.115	0.423	0.103	0.082	0.110
Savings deposit beta	0.322	0.789	0.385	0.245	0.375
Small time deposit beta	0.423	1.083	0.398	0.391	0.535
Large time deposit beta	0.539	1.436	0.614	0.465	0.644
Observations	18,871		889	7,665	7,664

Table 2: **Interest sensitivity matching**

Results 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. Standard errors are clustered at the bank and quarter level. The sample is from 1984 to 2013.

Δ Interest income rate

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum \gamma_\tau$	0.093***		0.003		-0.053		-0.065	
	(0.031)		(0.042)		(0.050)		(0.050)	
$\Delta \widehat{IntExp}$	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)
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 clust.	18,552	18,552	1,733	1,733	860	860	157	157
Time clust.	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 rate sensitivity of ROA**

Results from the following two-stage ordinary least squares regression of return on assets (ROA) on interest expense rates:

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

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. Standard errors are clustered at the bank and quarter level. The sample is from 1984 to 2013.

Δ ROA

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum \gamma_\tau$	0.044***		0.031*		0.030		0.036	
	(0.013)		(0.016)		(0.019)		(0.033)	
$\Delta\widehat{IntExp}$	−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)
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 clust.	18,552	18,552	1,733	1,733	860	860	157	157
Time clust.	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: **Market power and interest sensitivity matching**

Results from the following two-stage ordinary least squares regression of interest income rates on interest expense rates:

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

where X is market concentration (columns (1) and (2)) and bank market share (columns (3) and (4)). To calculate market concentration, we first construct a Herfindahl index of bank branches at the zip code level, then average them across all zip codes where a bank operates branches. To calculate a bank's market share, we average its share of the branches in each zip code where it operates. Columns (2), and (4) include time fixed effects. The sample is from 1994 to 2013.

Stage 1:	Market concentration		Bank market share	
	(1)	(2)	(3)	(4)
$\sum \beta_\tau$	−0.084***	−0.103***	−0.085***	−0.103***
	(0.021)	(0.015)	(0.020)	(0.015)
R^2	0.195	0.236	0.195	0.237
Stage 2:	**Δ Interest income rate**		**Δ Interest income rate**	
	(1)	(2)	(3)	(4)
$\sum \gamma_\tau$	−0.044		−0.060	
	(0.071)		(0.069)	
$\Delta \widehat{IntExp}$	1.213***	1.222***	1.259***	1.265***
	(0.178)	(0.151)	(0.176)	(0.148)
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
R^2	0.087	0.122	0.088	0.122
Observations	624,481	624,481	624,481	624,481
Bank clusters	13,019	13,019	13,019	13,019
Time clusters	80	80	80	80

Table 5: **Retail deposit betas and interest sensitivity matching**

Results from the following two-stage ordinary least squares regression of interest income rates on interest expense rates:

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

where X is bank retail deposit beta (columns (1) and (2)) and bank retail deposit beta using within-bank estimation (column (3) and (4)). Retail deposit betas are calculated at the MSA level using Ratewatch data for interest checking, $25k money market accounts and $10k 12-month CDs, then averaged across MSAs for each bank-product and finally across product for each bank. Retail deposit betas using within-bank estimation impose bank-MSA fixed effects in the first step of this estimation in order to control for differences in lending opportunities across banks. Columns (2) and (4) include time fixed effects. Standard errors are clustered at the bank and quarter level. The sample is from 1994 to 2013.

Stage 1:	Retail deposit beta		Retail beta, within-bank	
	(1)	(2)	(3)	(4)
$\sum \beta_\tau$	0.433***	0.455***	0.225***	0.209**
	(0.059)	(0.056)	(0.085)	(0.084)
R^2	0.197	0.240	0.197	0.239
Stage 2:	**Δ Interest income rate**		**Δ Interest income rate**	
	(1)	(2)	(3)	(4)
$\Delta \widehat{IntExp}$	1.408***	1.372***	1.191**	1.175**
	(0.242)	(0.223)	(0.561)	(0.586)
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
R^2	0.093	0.121	0.093	0.121
Obs.	318,650	318,650	318,650	318,650
Bank clust.	7,328	7,328	7,328	7,328
Time clust.	80	80	80	80

Table 6: **Maturity transformation and expense betas**

Panel regressions of the repricing maturity of loans and securities on interest expense betas and controls. Repricing maturity is a weighted average of the amounts reported within each interval. Wholesale funding is large time deposits plus Fed funds purchased and securities sold under agreements to repurchase plus brokered deposits. The betas are estimated by regressing the change in a bank's interest expense rate on the contemporaneous and previous three quarterly changes in the Fed funds rate. They are winsorized at the 5% level. Only banks with at least 20 quarterly observations are included. Top 5% of banks (Panel B) are those that have a top-5% average rank by assets over the sample. Standard errors are clustered at the bank and quarter level. The sample is from 1997 to 2013.

Panel A: All banks

	Repricing maturity				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−3.979***	−3.747***	−4.286***	−4.962***	−4.770***
	(0.240)	(0.238)	(0.242)	(0.245)	(0.246)
Wholesale funding ratio		−0.603***			−1.038***
		(0.181)			(0.176)
Equity ratio			−3.473***		−2.457***
			(0.486)		(0.501)
log Assets				0.238***	0.235***
				(0.017)	(0.017)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	472,834	472,834	472,834	472,834	472,834
Bank clusters	8,703	8,703	8,703	8,703	8,703
Time clusters	67	67	67	67	67
R^2	0.118	0.119	0.123	0.139	0.144

(continued on next page)

Table 6—*Continued*

Panel B: Top 5%

	Repricing maturity				
	(1)	(2)	(3)	(4)	(5)
Interest expense beta	−4.787***	−5.346***	−5.405***	−5.027***	−6.136***
	(1.347)	(1.477)	(1.285)	(1.397)	(1.489)
Wholesale funding ratio		2.353*			1.886
		(1.409)			(1.321)
Equity ratio			−13.421***		−12.720***
			(1.988)		(1.867)
log Assets				0.062	0.081
				(0.078)	(0.078)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	13,293	13,293	13,293	13,293	13,293
Bank clusters	259	259	259	259	259
Time clusters	67	67	67	67	67
R^2	0.049	0.065	0.108	0.051	0.119

Table 7: **Securities share and expense betas**

Panel regressions of the share of securities to assets on interest expense betas and controls. Wholesale funding is large time deposits plus Fed funds purchased and securities sold under agreements to repurchase plus brokered deposits. The betas are estimated by regressing the change in a bank's interest expense rate on the contemporaneous and previous three quarterly changes in the Fed funds rate. They are winsorized at the 5% level. Only banks with at least 20 quarterly observations are included. Top 5% of banks are those that have a top-5% average rank by assets over the sample. Standard errors are clustered at the bank and quarter level. The sample is from 1984 to 2013.

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

(continued on next page)

Table 7—*Continued*

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 8: **Interest rate sensitivity of securities**

This table shows results from the following two-stage ordinary least squares regression of interest income rates on interest expense rates:

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

where X is 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)). Columns (2), (4), (6), and (8) include time fixed effects. Standard errors are clustered at the bank and quarter level. The sample is from 1984 to 2013.

	Total securities		Treasuries & agency debt		MBS		Other securities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum \gamma_\tau$	0.049		0.090**		−0.034		−0.124***	
	(0.040)		(0.040)		(0.067)		(0.024)	
$\Delta \widehat{IntExp}$	0.593***	0.579***	0.445***	0.438***	0.522***	0.505***	0.523***	0.519***
	(0.043)	(0.044)	(0.054)	(0.054)	(0.079)	(0.079)	(0.066)	(0.067)
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	322,147	322,147	279,691	279,691	302,672	302,672
Bank clust.	18,448	18,448	8,908	8,908	8,051	8,051	8,442	8,442
Time clust.	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 9: **Interest rate sensitivity of securities, top 5% of banks**

This table shows results from the following two-stage ordinary least squares regression of interest income rates on interest expense rates:

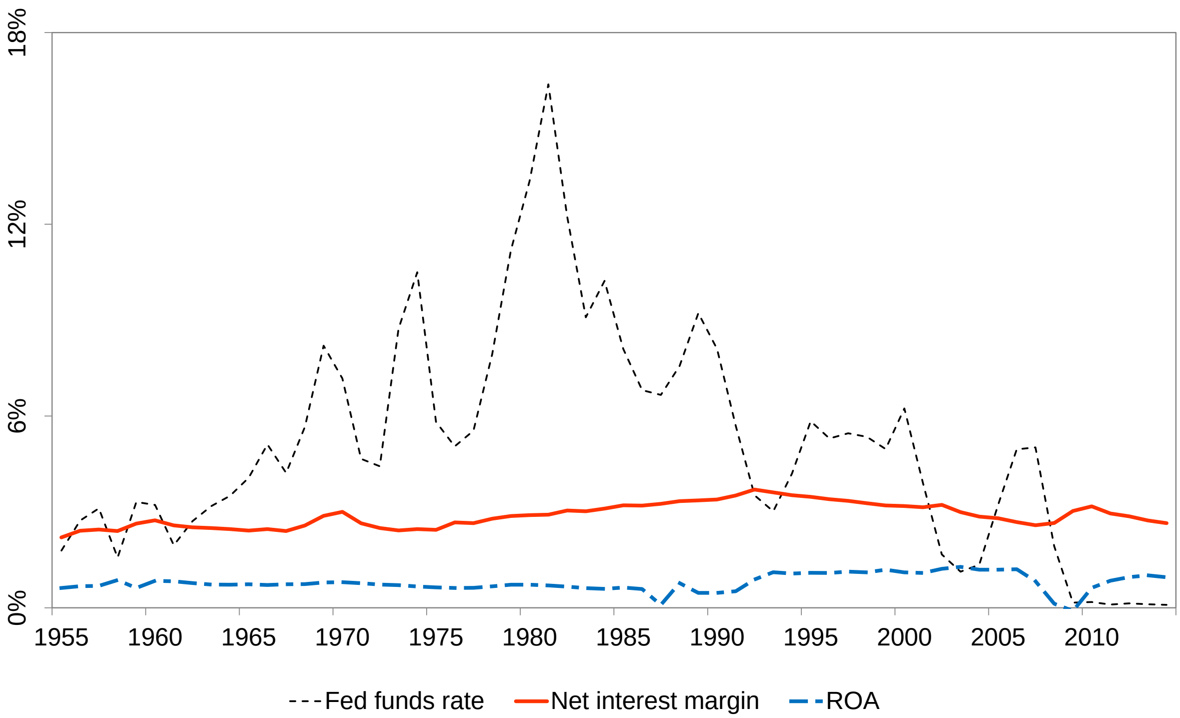
$$\begin{aligned} \Delta IntExp_{i,t} &= \alpha_i + \textstyle\sum_{\tau=0}^{3} \beta_{i,\tau} \Delta FedFunds_{t-\tau} + \epsilon_{i,t} && \text{[Stage 1]} \\ \Delta IntIncX_{i,t} &= \lambda_i + \textstyle\sum_{\tau=0}^{3} \gamma_\tau \Delta FedFunds_{t-\tau} + \delta \Delta \widehat{IntExp}_{i,t} +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

where X is 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)). Columns (2), (4), (6), and (8) include time fixed effects. Top 5% of banks are those that have a top-5% average rank by assets over the sample. Standard errors are clustered at the bank and quarter level. The sample is from 1984 to 2013.

	Total securities		Treasuries & agency debt		MBS		Other securities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum \gamma_\tau$	−0.166**		−0.008		−0.401**		−0.221**	
	(0.067)		(0.105)		(0.156)		(0.105)	
$\Delta \widehat{IntExp}$	0.949***	0.933***	0.803***	0.810***	1.339***	1.365***	1.013***	1.034***
	(0.141)	(0.142)	(0.225)	(0.223)	(0.358)	(0.367)	(0.243)	(0.242)
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	8,876	8,876	9,333	9,333	9,417	9,417
Bank clust.	857	857	281	281	282	282	285	285
Time clust.	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

Figure 1: **Aggregate time series**

The figure plots the aggregate time series of net interest margin (NIM) and return on assets (ROA) against the Fed funds rate. The underlying data is annual from FDIC, 1955 to 2015.



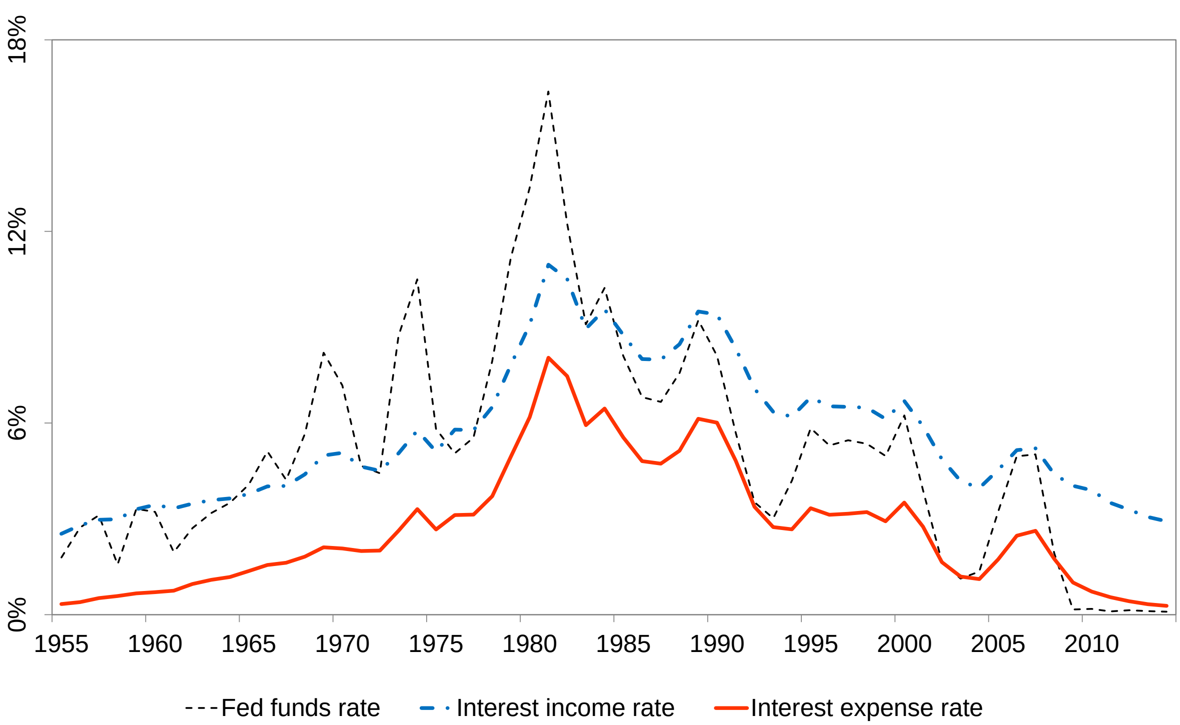


Figure 2: **Industry-level stock returns and interest rate changes**

The underlying 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) around FOMC meetings. We use a two-day event window as in Hanson and Stein (2015). The sample includes all scheduled FOMC meetings from 1994 to 2008 (there were 113 such meetings and 5 unscheduled ones).

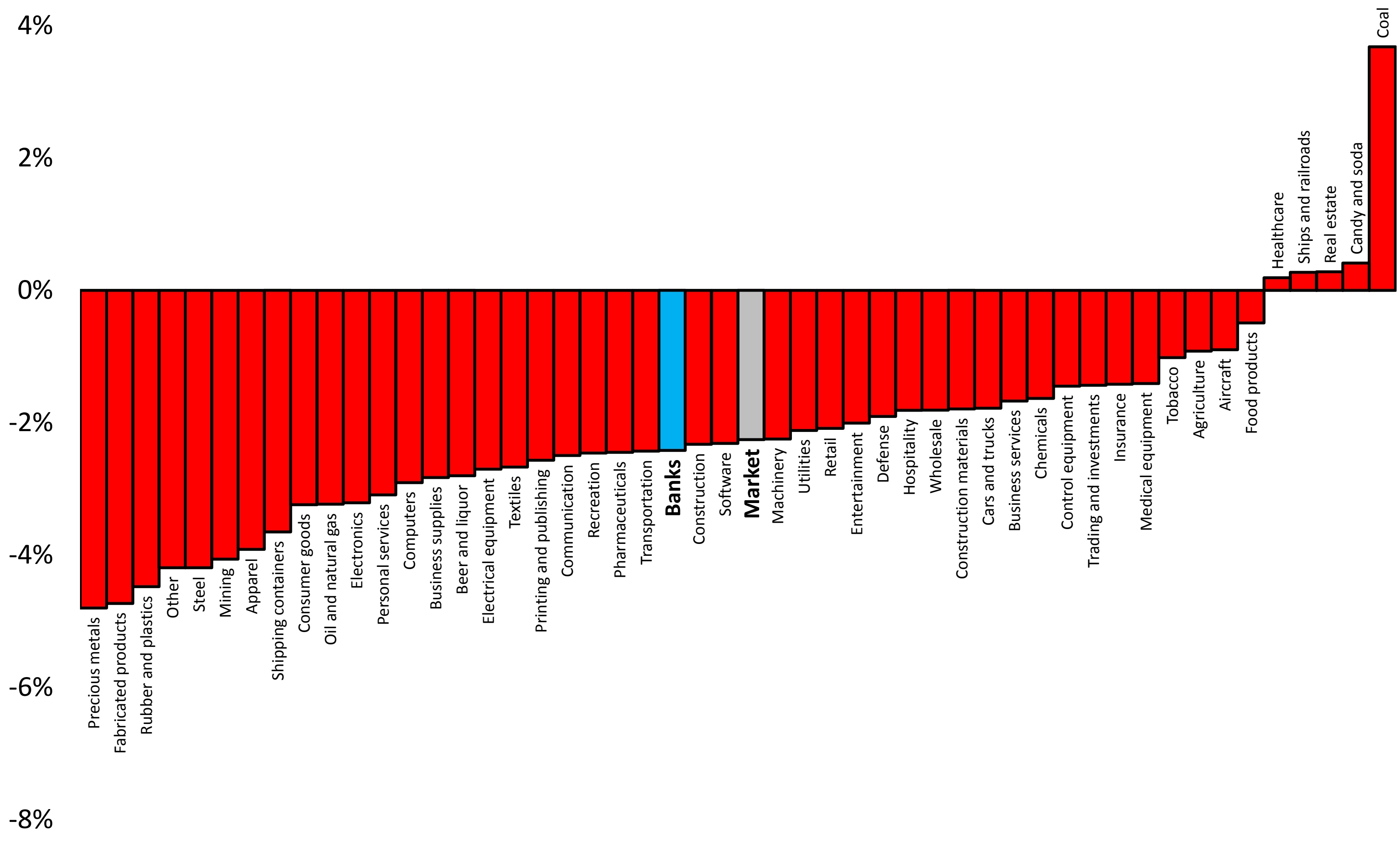
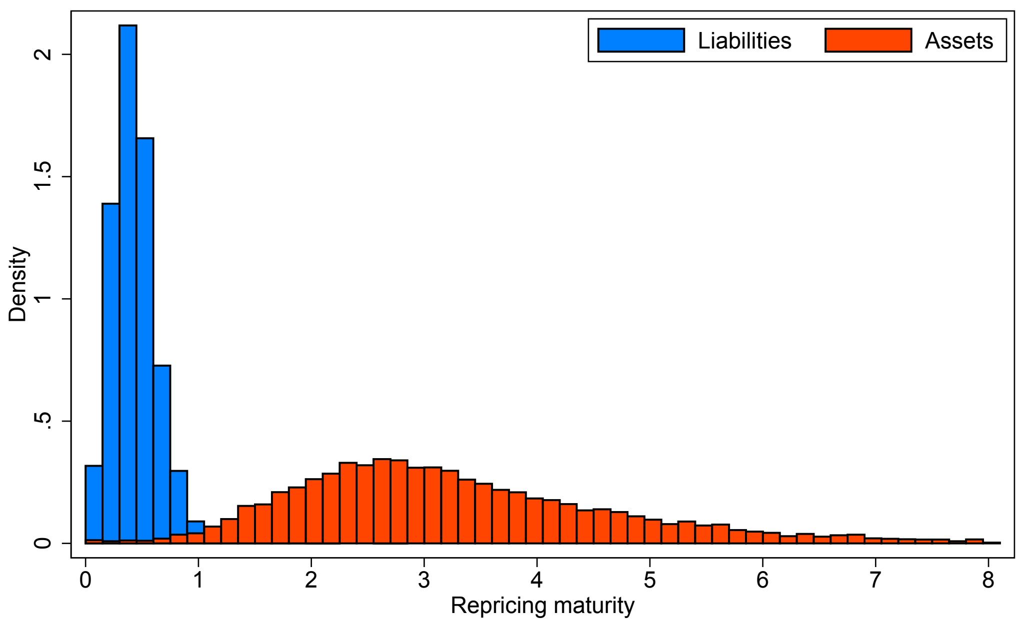


Figure 3: **Repricing maturities of assets and liabilities**

Asset repricing maturity is estimated by assigning zero repricing maturity to cash and Fed funds sold, and calculating the repricing maturity of loans and securities using the available data. Liabilities repricing maturity 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.

All banks



Top 5%

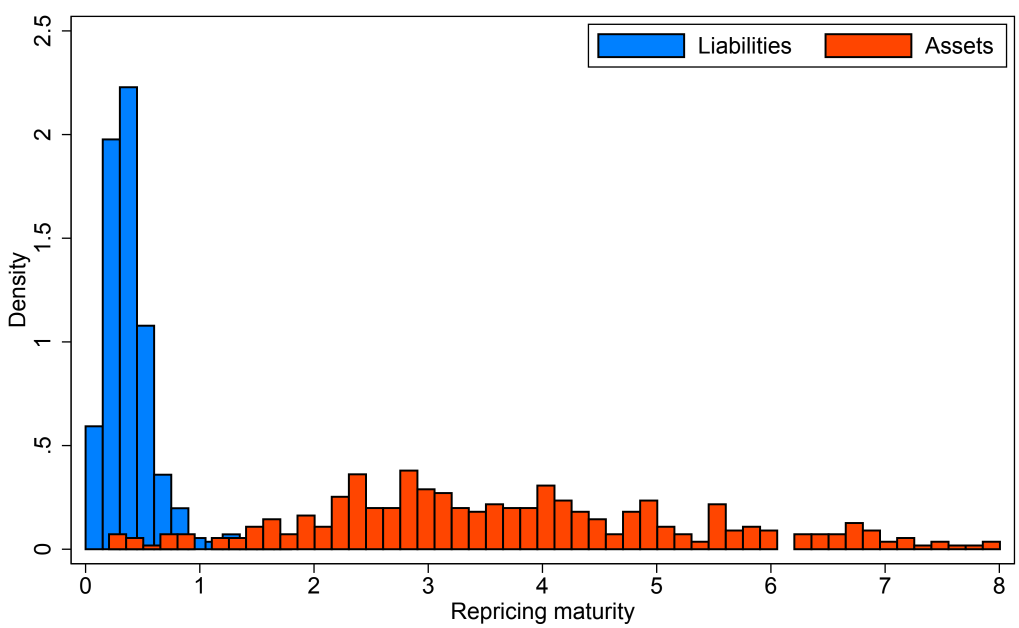
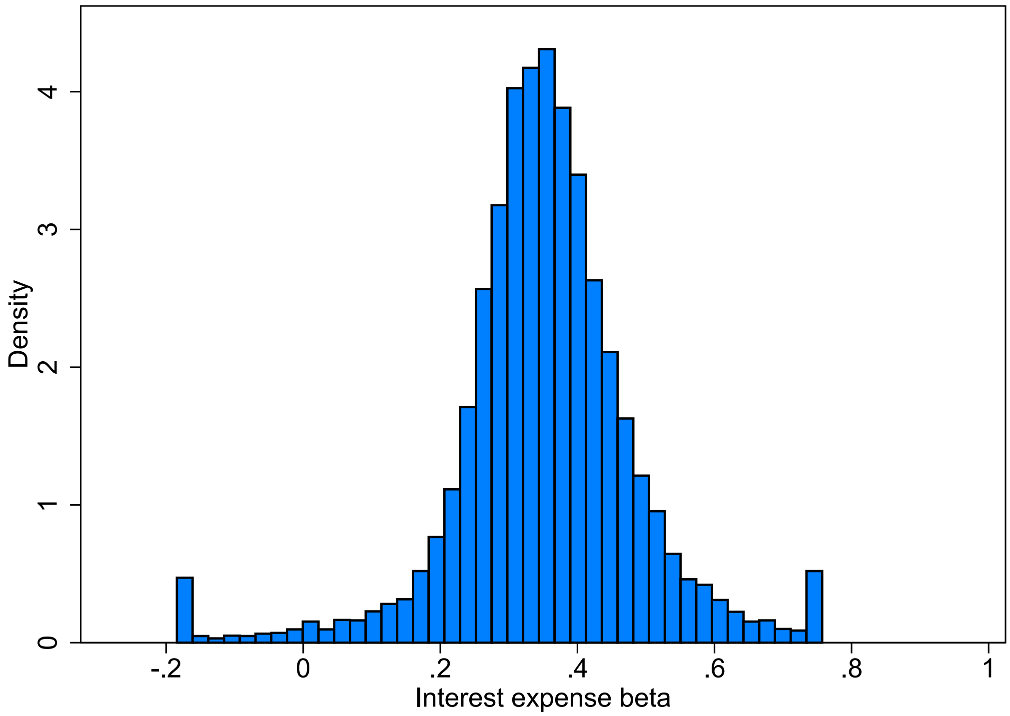


Figure 4: **The distributions of interest expense and interest income betas**

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 the purposes of this figure, the betas are winsorized at the 1% level.



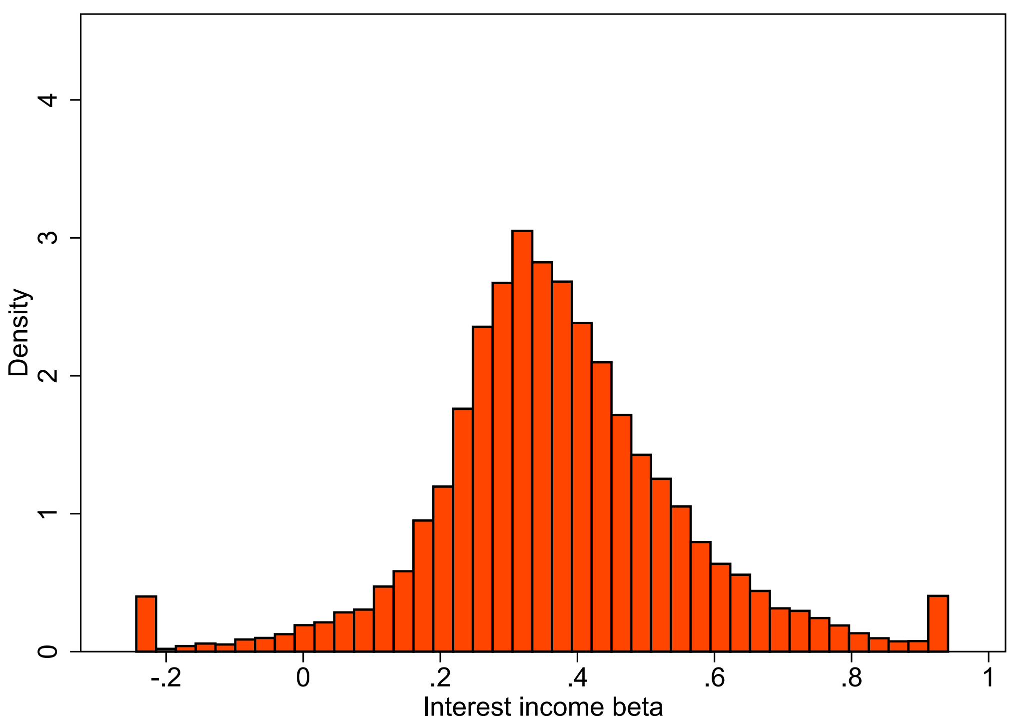


Figure 5: **Interest expense, interest income, and ROA matching**

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.

All banks | Top 5%

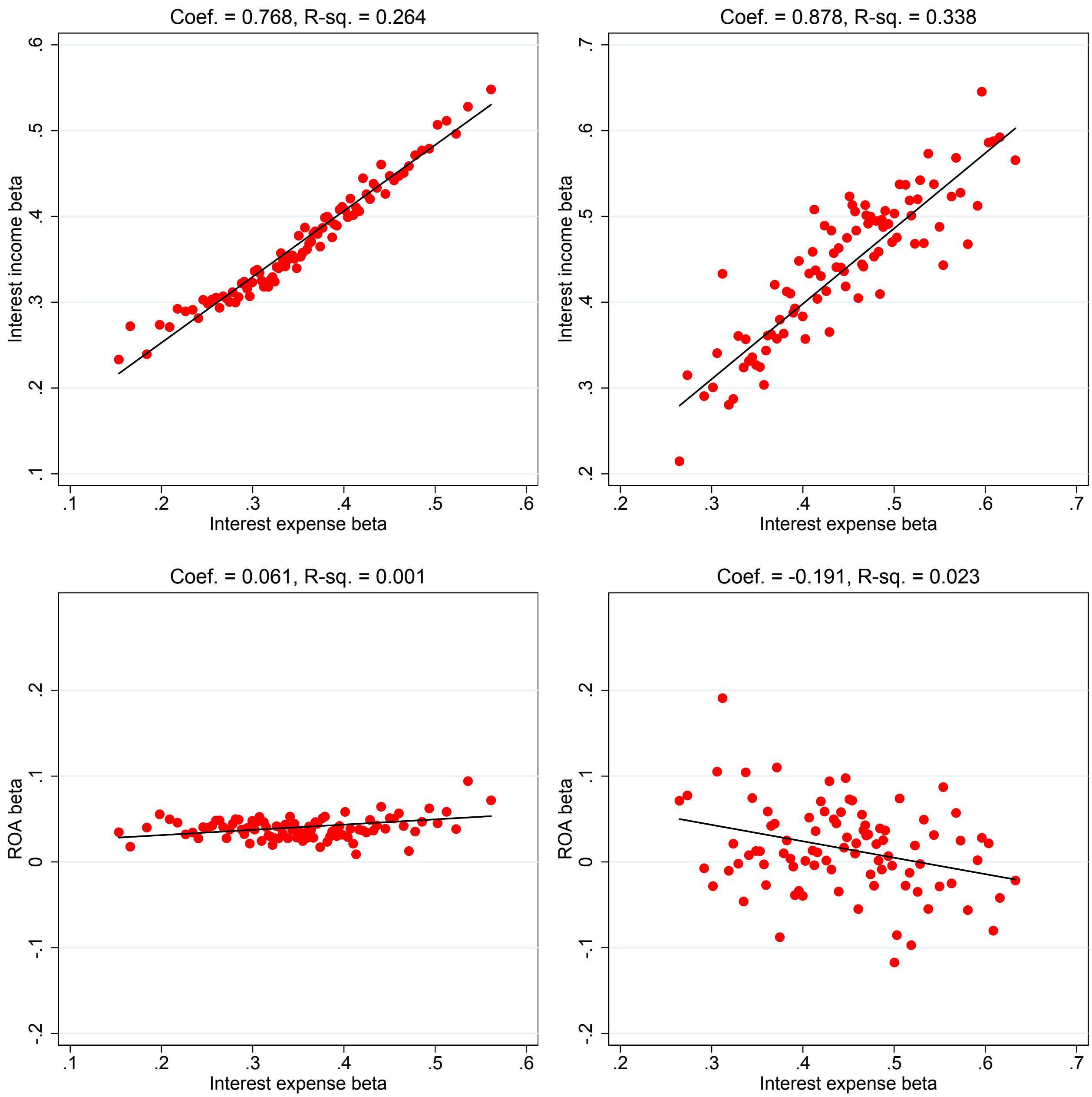


Figure 6: **Equity FOMC betas and interest expense and income betas**

This figure shows bin scatter plots of FOMC betas on interest expense and interest income betas for bank holding companies. The expense and income betas are calculated by regressing the quarterly change in each bank's interest expense or income rate on the contemporaneous and previous three changes in the Fed funds rate. The FOMC betas are calculated by regressing the stock return of publicly listed bank holding companies on the change in the one-year Treasury rate over a two-day window around scheduled FOMC meetings. The betas are winsorized at the 5% level. The bin scatter plot groups the 790 bank holding companies into 20 bins by interest expense or income beta and plots the average FOMC beta within each bin. The sample is from 1994 to 2008.

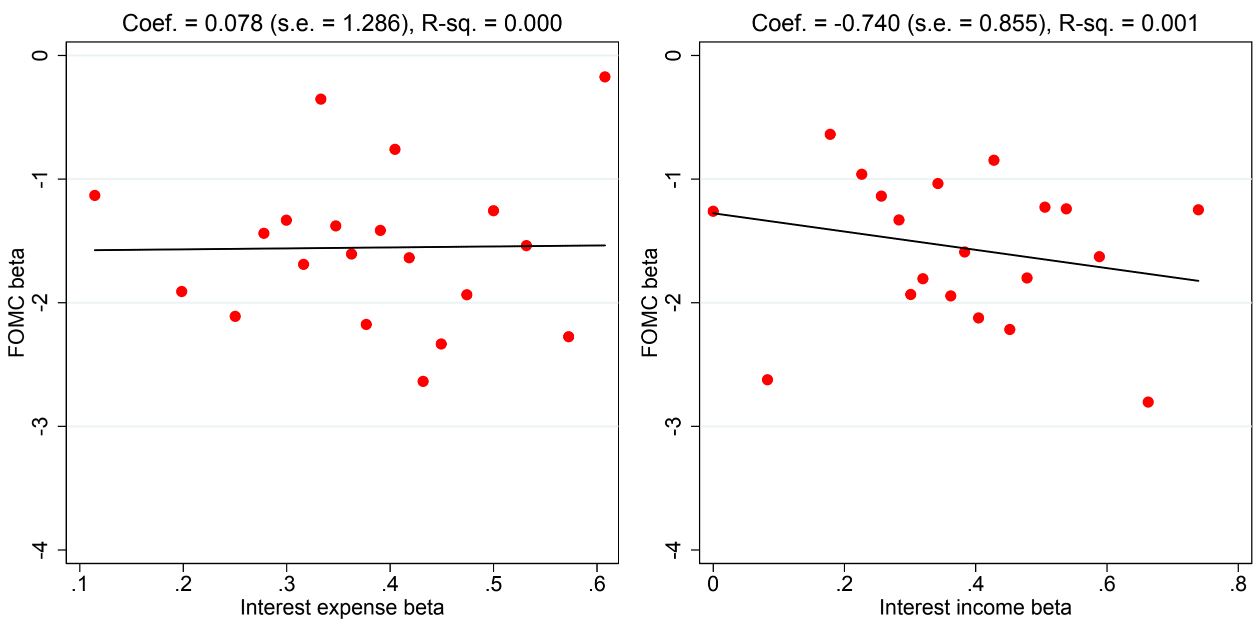
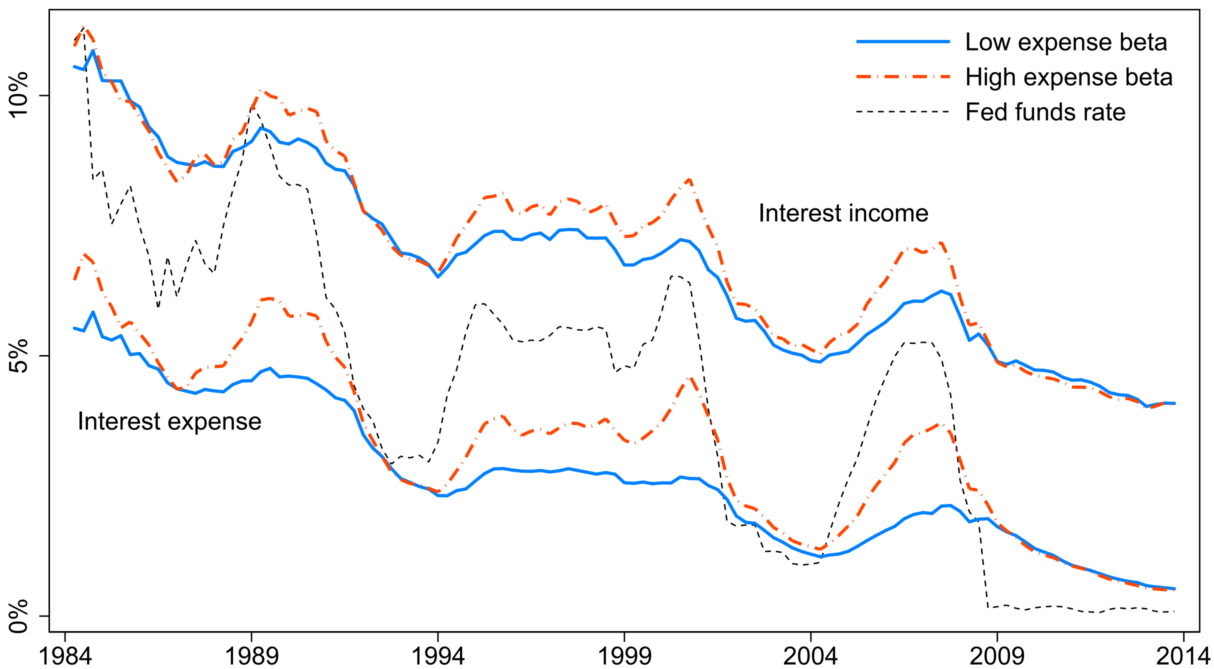


Figure 7: **Interest income and expense rates, net interest margin, and ROA by expense beta.**

The time series of interest income and expense rates, net interest margin, and return on assets (ROA) for banks with low and high interest expense betas. We sort banks into twenty bins by interest expense betas, then average interest income and interest expense within each bin and quarter. 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.



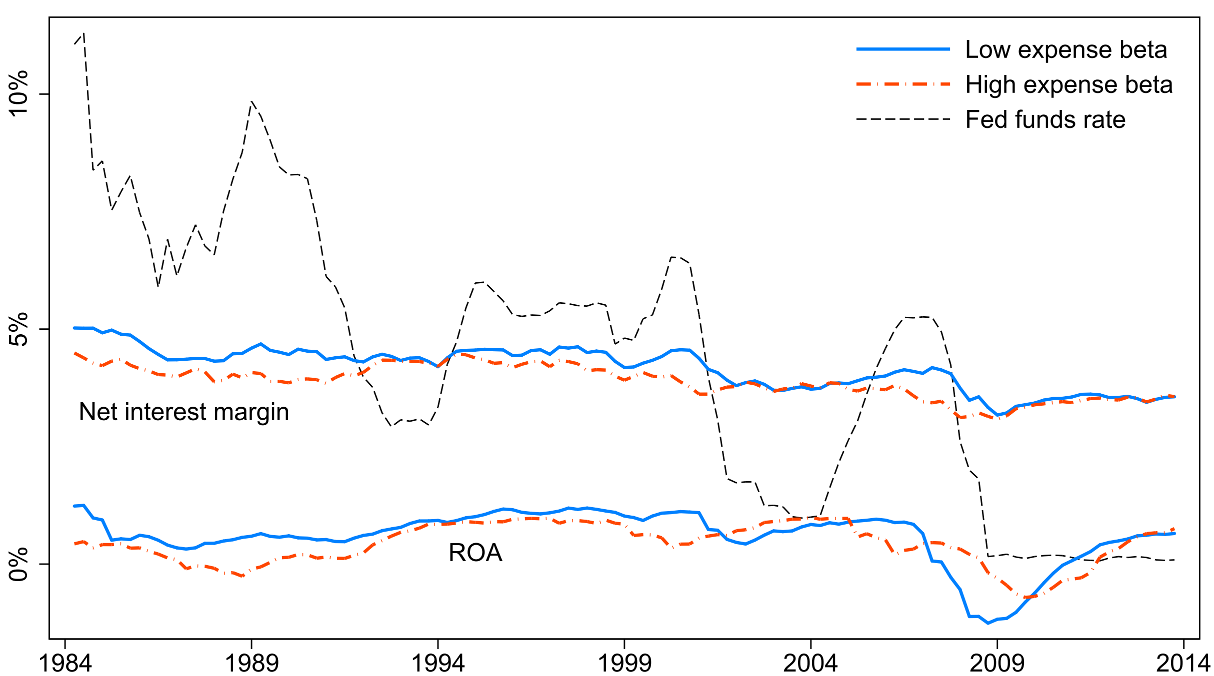


Figure 8: **Interest expense betas and market concentration**

This figure presents bin scatter plots of interest expense betas and savings deposit interest expense betas on zip-code level Herfindahl indexes and bank market share. The Herfindahl index is constructed in two steps. In the first step, we take the number of branches of each bank in a given zip code and divide by the total number of branches in the zip code, then square and sum these shares to get a zip-code Herfindahl. The second step is to average these zip-code Herfindahl indexes across all zip codes where a given bank has branches, weighting each zip code by the number of branches that the bank has in that zip code. Banks' market shares are similarly constructed by averaging a bank's share of all branches in a given zip code and weighting by the number of branches the bank has in that zip code. 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.

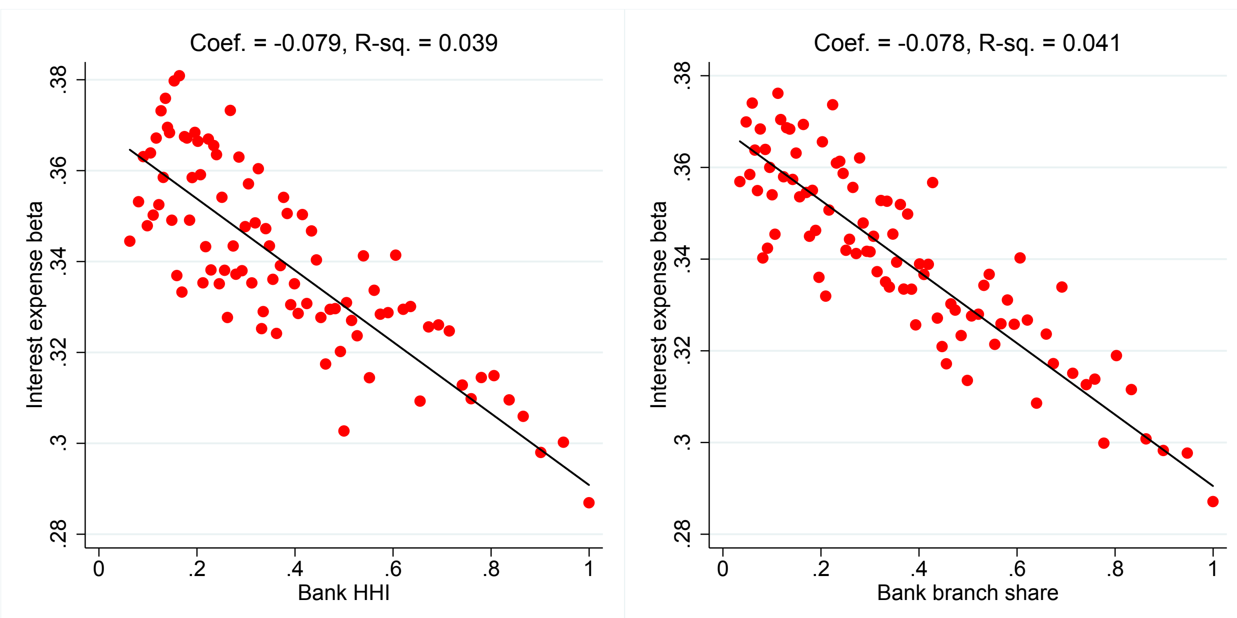


Figure 9: **Interest expense betas and bank deposits per branch**

This figure presents bin scatter plots of interest expense betas and savings deposit interest expense betas on banks' log deposits per branch ratio. Deposits are in millions hence a bank with a log deposit per branch ratio of 2.5 or 4.5 has about \$12 million or \$90 million of deposits per branch, respectively. 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. The sample covers 1994 to 2013, when the FDIC branch-level data is available. Only banks with at least 20 quarterly observations over this period are included. The betas are winsorized at the 5% level.

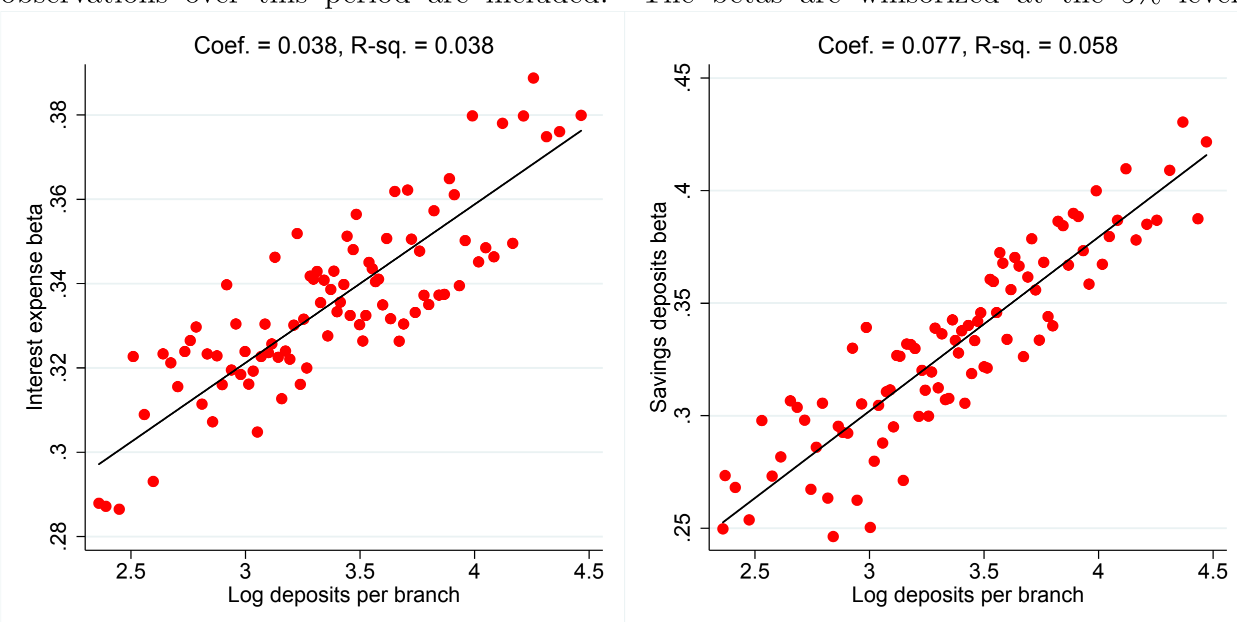
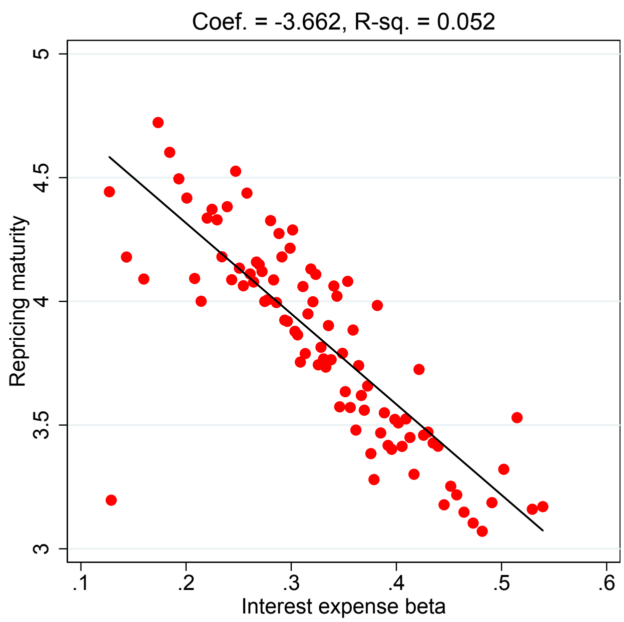


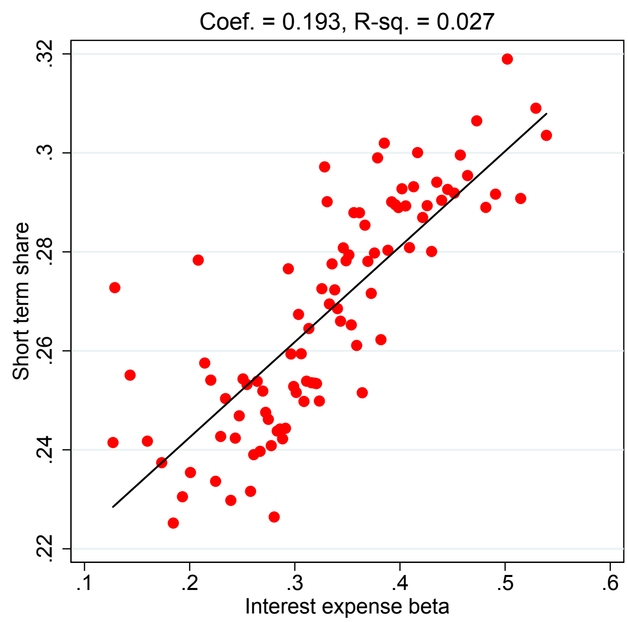
Figure 10: **Maturity transformation and derivatives usage**

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.

Repricing maturity



Short term share



Appendix

Table A.1: **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

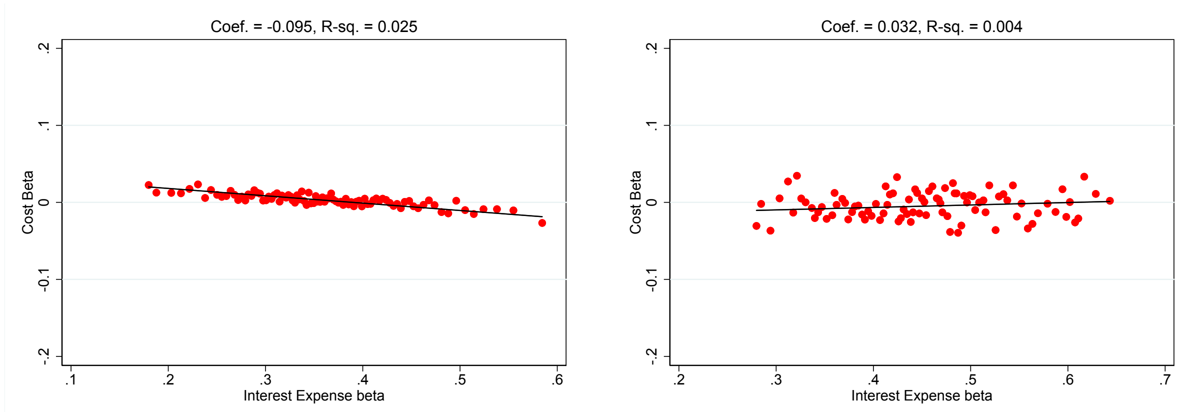
	All banks		No derivatives		Nonzero derivatives	
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum \gamma_\tau$	−0.011		−0.007		−0.090**	
	(0.030)		(0.029)		(0.039)	
$\Delta\widehat{IntExp}$	1.108***	1.114***	1.096***	1.104***	1.305***	1.323***
	(0.056)	(0.055)	(0.055)	(0.054)	(0.071)	(0.073)
Bank FE	Yes	Yes	Yes	Yes	Yes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

Figure A.1: **Operating Costs and Deposit Fee Income by expense beta**

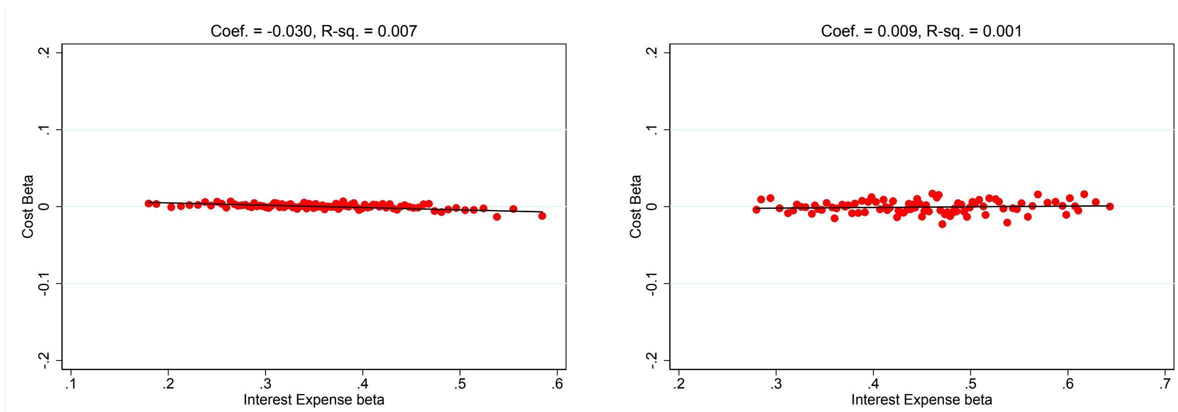
This figure shows bin scatter plots of bank operating costs and deposit fee income by expense betas. The betas and scatterplots are constructed the same was as in Figure 5. The left column is for all banks and the right column for the top five percent of banks. The top panel provides information on total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