SENSITIVITY MATCHING THROUGH MARKET POWER

BANK HEDGING IN THE AGE OF LOW INTEREST RATES

EDVIN LANDVIK

ERIC SEGER ELLSÄTER

Bachelor Thesis

Stockholm School of Economics

2020

Sensitivity Matching Through Market Power: Bank Hedging in the Age of Low Interest Rates

Abstract:

We replicate the paper of Drechsler et al. (2017a) who find that banks are able to hedge against interest rate risk exposure through maturity transformation. Our results confirm their findings prior to the financial crisis that the interest sensitivities of income and expenses closely follow one another, resulting in an insensitive ROA. In the following period of low interest rates banks are unable to use maturity transformation as a hedge. The interest income exposure turns negative and banks can therefore not match the sensitivity sufficiently to hedge their exposure.

Keywords:

Maturity Transformation, Risk Exposure, Interest Rate Risk, Financial Crisis, Maturity Mismatch, Bank Returns

Authors:

Edvin Landvik (23980)
Eric Seger Ellsäter (23206)

Tutors:

Adrien d'Avernas, Assistant Professor, Department of Finance

Examiner:

Adrien d'Avernas, Assistant Professor, Department of Finance

Bachelor Thesis
Bachelor Program in Business and Economics
Stockholm School of Economics

We would like to thank Adrien d'Avernas, Emelie Fröberg, David Montag and Georg von Zweigbergk for their support.

1 Introduction

A common view of banks is that they differ fundamentally from other industries (Fama and French, 1992), not least in terms of the exposure to interest rate risk. This notion stems from banks' practice of maturity transformation, which according to textbook models should result in a significant sensitivity to interest rate changes. The maturity mismatch that arises when borrowing short term and simultaneously lending long term means that even relatively small increases in the short term interest rate would be catastrophic for banks' interest margins and in extension their equity value. Surprisingly, when examining bank stock returns, even in periods of significant interest rate fluctuation, the effects on bank equity have not been nearly as severe as expected. A number of articles and models have been presented trying to explain this mismatch by further analysing banks' exposure to interest rate risk, but with conflicting results and conclusions. Using the methodology of Drechsler et al. (2017a) we investigate whether or not their model of market power as an explanation for the low interest rate risk of banks yields similar results to other methods.

The main question is whether or not the results of Drechsler et al. (2017a) still hold in a low-interest rate environment. Several papers point to lower rates eroding bank net interest margins (NIM) and by extension profitability. Bailey and Matyaš (2019) even find that the interest rate sensitivity reverses for returns on bank stocks. Within the framework of Drechsler et al. (2017a) this might be indicative of banks' inability to pass on costs to their retail deposit customers in the form of an interest rate gap. We thus seek to investigate the occurrence of such a reversal when applying their model.

The phenomenon of interest matching has implications for the transmission of monetary policy. Drechsler et al. (2017b) show that banks use their market power to expand the difference between deposit rates and the fed funds rate. Similarly Gomez et al. (2019) find that banks with a higher income gap reduce their lending by less in response to interest rate changes. Lower interest risk could also shield banks from the effect of the balance sheet channel proposed by Bernanke and Gertler (1995).

In this paper, we use the model proposed and empirical framework of tests used by Drechsler et al. (2017a). Their model describes bank's investment decisions and how the use of market power enables banks to hedge through maturity transformation. Following the model predictions we run a series of regressions to the test its explanatory power. First, we replicate the findings of their paper to confirm the validity of our application method and their results. The replication then serves as the basis for further analysis and tests.

We find that banks match their interest income and expense rates relatively closely with few exceptions before the financial crisis. Our results closely match those of Drechsler et al. (2017a). After the financial crisis, the relationship is substantially altered; they fail to hedge their exposure. Our analysis shows that banks can no longer use their market power over deposit expenses to match the interest sensitivity of their income. As a consequence the interest rate sensitivity of the return of assets (ROA) increases.

2 Literature Review

The nature of bank stock returns, and more specifically their exposure to risk, is an area of contention within the academic literature. Several papers have explored whether banks have a different risk exposure than other industries. These differences include credit risk (Begenau et al. 2015) and interest rate risk (Begenau et al. 2015, Flannery and James 1984). More recently, Bailey and Matyaš (2019) show that bank stock returns are sensitive to the overall market risk and further confirm that banks are indeed sensitive to interest rate changes. In agreement with these findings, Claessens et al. (2018) demonstrate that the net interest margin of banks decreases with lower interest rates. On the contrary, earlier findings of Flannery (1981) point to low exposure to interest rate changes.

Still, the traditional view is that banks' return is subject to short-term interest risk exposure (Flannery and James 1983). This exposure is thought to arise from the maturity mismatch between the short-term liabilities, in the form of deposits, and the longer-term assets (Diamond 1984, Rajan and Stein 2002). In stark contrast, Drechsler et al. (2017a) conclude that accounting profitability measures such as NIM and consequently ROA are largely insulated from changes in the short-term interest rate. They state that maturity transformation is the process through which they hedge interest rate risk due to banks altering the character of their deposits. Banks' draw market power from the deposit franchise operations which they use to impose a gap between the short-term interest rate and their deposit rates. Hence, it enables them to utilize maturity transformation as a method to manage risk.

The literature is also divided on the special nature of banks' deposit operations. Similarly to Drechsler et al. (2017a), Di Tella and Kurlat (2017) find that deposit rates are insensitive to the risk of the short-term interest rate, even if the explanation (i.e. capital constraints) differs. This is consistent with a large portion of the literature stating that bank deposits exhibit low interest-rate sensitivity (Hannan and Berger, 1991, Driscoll and Judson 2013), providing a cost advantage.

Fama (1985) argues for the general notion of deposits constituting a distinguishing edge for banks, but this edge is derived from an information advantage. Contrasting with the previous literature, Stafford (2019) finds that any cost advantage has diminished over time, and the results of Begenau and Stafford (2018) show that there is no advantage if the associated operating costs are taken into account.

Another dimension is the impact of interest rate on risk exposure. In times of exceedingly low interest rate, such as the post-crisis period, the sensitivity of net interest margins increases (Claessens et al. 2018) and the impact on risk exposure increases over a protracted period of low rates. Bailey and Matyaš findings on stock returns are consistent with this, but their results indicate that it might mainly be due to the slope of the yield curve rather than the level. After 2008 the absolute magnitude of the interest rate sensitivity increases, and the relationship turns from positive to negative. They also reason that a possible explanation could be that there is a zero lower bound on deposit rates. Thus, banks are unable to counteract their risk exposure on the income side by imposing a gap on their main source of funding. This is further supported by Brunnermeier and Koby (2019) who find that the deposit supply elasticity becomes greater as rates fall, reducing any advantage of deposits.

Our contribution to the literature is to enhance the understanding of banks' interest rate risk exposure and their management of that risk within the framework of Drechsler et al. 2017. First, we replicate their findings with an extended time period up to 2019 and we also include a replication of the same period in the appendix. The replication serves as a basis for further analysis.

Secondly, we investigate whether their findings hold over time. In particular we examine the impact of a low interest rate environment on the sensitivity matching in the post-financial crisis period to see whether the results match those of Bailey and Matyaš (2019). It would mean that they cannot hedge their risks. Furthering the research in this area would have implications for knowledge of bank returns, bank interest rate risk and by extension the impact of monetary policy on banks (Drechsler et al. 2019).

3 Data

Federal Funds effective rate

The effective Federal funds rate is obtained as a monthly average time series via the H.15 release from the Federal Reserve Board. To obtain a quarterly time series we select only the data points corresponding to the last month of each quarter. The data includes the years 1960-2019.

U.S Call reports

Quarterly time series bank data is obtained via Wharton Research Data Services (WRDS) from January 1984 to September 2019. Variable selection is identical to that of Drechsler et. al (2017a) and contains quarterly observations of income and balance sheet items from all commercial U.S banks. To create a consistent time series across the entire time frame , we replicate the data-cleaning procedure published by Drechsler et. al (2017a). When calculating repricing maturities, they apply the method of English et al. (2012). This paper uses the same method.

When obtaining data manually from WRDS, and following the cleaning procedure, a significant number of variables are missing data from 2011 and onwards. To construct a complete dataset we therefore let the type of report filed (RCON9804) determine which variable series to use when constructing the remainder of the data series. Banks that filed either the FFIEC 041 or FFIEC 059 utilise the RCON series of variables, while all other reporting types in our sample utilise the RCFD series. This process yields a complete dataset that covers the entire time frame of 1984-2019, excluding the fourth quarter of 2019.

Branch-level deposits

The Federal Deposit Insurance Corporation (FDIC) database is used to obtain annual data on branch-level deposits from 1994 to 2019. The dataset covers all U.S bank branches and provides information on key branch characteristics. Using the unique financial institution identifier, RSSD ID, we match the data to the above described call reports dataset.

4 Model

As the replication constitutes the major part of this paper and serves as the basis for further analysis, naturally we follow the same methodology as Drechsler et al. (2017a). They present a model for explaining the investments of banks. It is based on a set of assumptions: the discretization of time, infinite time horizon and the only source of funding is short-term risk-free deposits. For simplifying reasons, banks do not issue equity. If banks remain profitable there is no need. In this model, banks seek to maximize the discounted present value of their profits and are only constrained by maintaining a minimum solvency.

A key component of the model is the deposit franchises of banks, with a variable cost equal to a constant fraction of the deposits. The costs arise from investments in, and operations of, branch offices, personnel and marketing. From their franchises, banks derive market power which they use to impose a gap between the deposit rates paid to their clients and the short market rate as such:

$$\beta_t^{Exp} f_t \tag{1}$$

where β_t^{Exp} assumes values between zero and one, and f_t is the short-term interest rate. The more market power a bank enjoys, the lower the β_t^{Exp} and thus larger the gap. On the contrary, lower market power, e.g. a larger portion of wholesale deposits, corresponds to a higher β_t^{Exp}.

Assets, on the other hand, are determined by the stochastic discount factor, which is also used to discount profits. Asset markets are assumed to be complete. The investment problem banks face can be summarised by:

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

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

$$INC_t \geq \beta_t^{Exp} f_t + c \tag{4}$$

where INC_t is the income flow dependent on time and state. The deposits are normalized to one dollar and constitute the budget constraint; in present value terms the income stream must equal their liabilities in the form of deposits. This is depicted in equation (3), the solvency constraint, which states that bank profits must be non-negative, or cover their expenses (interest and operating).

An implication of the model is that banks are exposed to the risk that their interest rate expenses increase with the interest rate f_t, resulting in insolvency (as long as $\beta_t^{Exp} > 0$). Therefore they should match their expenses with an adequate share of assets with short-term maturities. The matched income flow allows them to always fully cover their costs and hedge their expense risk appropriately. A large β_t^{Exp} (closer to one) would be consistent with the view that maturity mismatching exposes banks to short-term interest rate risks. With increasing market power the gap widens (or β_t^{Exp} becomes larger), and thus the share of short-term sensitive assets need only be small.

Adding to this risk is the cost of running the franchise, which is constant and thus not sensitive to the short-term rate. The operating cost, c, is unaffected by changes in the short-term rate. Both these aspects must be accounted for in determining the composition of assets to fully hedge their exposure to interest rate risk. There is a balance between investing in sufficiently sensitive and insensitive assets to match the average sensitivities of the interest expenses and operating costs. Drechsler et al. (2017a) summarizes these considerations in the following proposition:

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

$$INC_t \geq \beta_t^{Exp} f_t + c \tag{5}$$

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

$$\beta_t^{Exp} = \frac{\partial INC_t}{\partial f_t} = \beta_t^{Exp} \tag{6}$$

With no excess profits or rents, the net present value of the additional costs and the savings from the interest gap attributable to the franchise must equal zero. The entirety of the income must be devoted towards covering the costs, and in order to not risk insolvency it must match the income and expense short-term interest rate sensitivities. An implication of (5) is that the share invested in short-term can equal β_t^{Exp} and the remainder in longer-term assets.

Using the predictions of the model as guidelines, we perform the same regressions as Drechsler et al. (2017a), which include some of their robustness tests. The main prediction of the model is that banks must manage the matching of the interest rate sensitivity of their income and expenses. We check this by directly comparing the respective betas and regressing one on the other using panel data. Banks implement this by adjusting their asset composition accordingly. Lastly, we test the the relationship between market power and expense betas which is the model explanation of the phenomenon.

5 Empirical Analysis

5.1 Replication with extended timeframe

In the following sections we run a series of regressions, each of which serves to investigate the validity of the model predictions of Drechsler et al. (2017a). The tests are performed stepwise, and build upon one another: from the prediction of sensitivity matching to the use of market power, which enables hedging interest risk through maturity transformation. In every panel regression we double-cluster the standard errors by bank and quarter.

Sensitivity matching

One of the major predictions of the model introduced by Drechsler et al. (2017a) is that banks completely match their income and expense interest rate sensitivities. Consequently, the NIM and by extension ROA should remain relatively constant, as depicted in Figure 1: Panel A. In each of the following regressions in this section the sample extends from 1984 to the third quarter of 2019, and only includes banks with at least five years of observations. There is a section in the appendix on some minor filtering. Since all regressions on data from 1984 includes lagged Fed funds variables, we include Fed funds rate observations from 1983.

Cross-sectional analysis

We start the analysis by obtaining a measure of the interest rate sensitivity of bank expenses. It will serve as part of the initial analysis as well as input in later regressions. Changes in the interest rate expense is regressed on changes in the Federal Funds rate. For each individual bank, i, we perform the OLS time series regression below:

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

where $\Delta IntExp_{i,t}$ is the change in the interest expense rate from period t to period $t+1$. Likewise, FFR is defined as the change in the Fed funds rate from t to $t+1$. In addition, three lags of the Fed funds rate are added to include the full cumulative impact. The expense interest rate is calculated by dividing interest expenses by quarterly average assets and annualizing the ratio by multiplying by four. To obtain the individual sensitivity measure, all slope coefficients (betas) are added together for each bank separately.

The average is then calculated and winsorized at the five percent level, with a resulting beta of 0.361 and a standard deviation of 0.109. All results in this part are presented in table 1. Any value substantially below one would be consistent with the model. Short-term deposits are not the only source of funding of banks. It also includes longer-term liabilities such as time deposits and other short-term liabilities. Still, the results indicate predictions of the model are correct and also resemble that of Drechsler et al. (2017a) even though we extend the time period.

In order to examine whether banks engage in maturity transformation we require the equivalent interest income sensitivity measure. We rerun the regression above and substitute the change in interest income rate as the dependent variable. The winsorized average beta is 0.381 and the standard deviation is 0.167. There is quite substantial variation in terms of interest rate sensitivity, especially on the income side. The results are similar, with a difference of only 0.02, which again is consistent with the model. In fact, the model would not predict a perfect match as operating expenses are not included in this expense sensitivity measure.

The matching should also result in an insensitive NIM and consequently ROA. Regressing the unadjusted ROA[1], on the same explanatory variables yields a coefficient with the value 0.045 but a large standard deviation of 0.368. Table 1. also depicts differences between high and low beta and size, with characteristics of the groups similar to those in Drechsler et al. (2017a). Most noticeable is the small difference in average assets. In our table we only include banks that were included in the regression sample.

Panel analysis

We continue the analysis of sensitivity matching by complementing it with a panel analysis. It provides us with a more refined measure to assess banks' engagement in sensitivity matching. Contrary to the previous analysis, banks are weighted by the number of observations in panel regressions. As in Drechsler et al. (2017a) the analysis is conducted in two steps. First we make full use of equation (7) to estimate fitted values for each bank instead of simply summing the slope coefficients. In the second step we include the fitted values to estimate and run the following OLS panel regression:

$$\Delta IntInc_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_\tau \Delta FFR_{t-\tau} + \delta \Delta \widehat{IntExp_{i,t}} + \epsilon_{i,t} \quad (8)$$

where $\Delta IntInc_{i,t}$ and ΔFFR_t , including the lags, are defined as before, $\Delta\widehat{IntExp_{i,t}}$ is the value predicted using the previous regression and the intercept term λ_i is the individual fixed effect of the banks. In an alternative specification, time fixed effects , θ_t , are included in place of the Fed funds variables.

The model predicts that the interest expense coefficient should be one, or close to one as

[1]There are some seasonal changes in the unadjusted ROA measure which we use. For instance, the loan loss provisions are concentrated to the final quarter. Nonetheless, Drechsler et al. (2017a) state that their results are robust to seasonality which our results confirm, although the standard deviation is larger as a result.

not all expenses are included. In Table 2 the results are depicted.The fitted values have a coefficient of regardless of nearly 0.73 regardless the specification, which is close to Drechsler et al. (2017a). However, a sample with only the top 5% of banks by assets yields a result that differs more substantially from their findings, with a value of approximately 1.3 as compared to about 1, regardless of the two specifications[2]. The control interest rate variables are slightly larger but still small, but could still indicate a somewhat larger exposure to the interest rate than in Drechsler et al. (2017a)

The initial analysis indicates that banks on average do engage in sensitivity matching. The model predicts that they should match their expenses and income. Even though we would not expect full matching, because of the numerous assumptions, the results are clearly indicative of banks engaging in sensitivity matching. The interest income rate is only slightly larger than the interest expense rate sensitivity. Because the model also includes operating costs as part of the considerations for sensitivity matching, the model would not predict a complete matching of only interest income and expenses.

Asset duration and composition

Engaging in maturity transformation means that banks must adjust the composition of assets to reach an appropriate level of interest rate exposure on the income side. The duration of assets, or repricing maturity as a proxy, generally decides the interest sensitivity. A longer duration means less interest rate sensitivity and it is the method through which banks execute the matching. As a consequence we would expect to find that the repricing maturity decreases as the interest expense sensitivity increases, i.e. a negative relationship. We describe the method, which is the same as English et al. (2012) by which we calculate repricing maturities as a proxy for duration in the appendix. The same method is also used to calculate repricing maturity in Table 1. Accordingly, we estimate the following OLS panel

[2] One reason could be that Drechsler et al. (2017a) seem to use two different methods to divide banks by size. We consistently use the same method: taking the average assets across the sample period and ranking them.

regression:

$$RepricingMaturity_{i,t} = \alpha_i + \delta\beta_i^{Exp} + \sum_{j=0}^{3} \gamma_j X_{j,i,t} + \varepsilon_{i,t} \tag{9}$$

where $RepricingMaturity_{i,t}$ is the weighted average repricing maturity of assets, α_i is the individual fixed effect, β_i^{Exp} is each banks individual expense beta as estimated previously. In addition, $X_{i,t,j}$ denotes a set of control variables, which includes the wholesale funding share, calculated by adding the Fed funds purchased and repo to the large time and brokered deposits, the natural logarithm of assets and the equity ratio. We repeat the regression, but replace the control variables with time fixed effects η_t. The sample covers the period 1997-2019, as the FDIC reports submitted by banks over that interval contain the relevant data.

Table 3 shows that the beta coefficient is in the range of -3.03 to -3.83 depending on the specification. The results are consistent with the prediction, that banks adjust their risk exposure on the asset side in accordance with their expense exposure to the interest rate. This is similar to the average value in the cross section in Table 1. A bank with no short-term interest exposure would have a 3.83 years longer asset repricing maturity than a fully exposed bank if we control for wholesale funding, solidity and size. We arrive at a qualitatively consistent but smaller value than Drechsler et al. (2017a). It would seem that the degree to which banks respond to lower interest expense sensitivity is smaller.

Complementing the analysis we examine the impact on asset composition. Deciding the composition is the process through which banks execute sensitivity matching. Securities generally have a longer repricing maturity. Thus we would expect banks with a high interest expense beta to invest more in long-term assets such as securities and consequently the relationship to be negative. We rerun the regression, but substitute the security share for the repricing maturity, shown in table 4.

The resulting coefficient is between -0.19 and -0.25 depending on the specification. It indicates that the adjustment of the security share is related to the interest expense beta. In addition, the results can be used to dismiss another explanation for the matching sensitivities. Drechsler et al. (2017a) point out that it is plausible that higher exposure of expenses to interest risk is associated with higher liquidity risk. Therefore, banks match the short-term liabilities with short-term assets as a form of buffer. Securities are also by definition relatively liquid and could consequently be used to manage liquidity risk. The results show it that it does not appear to be a viable explanation, with the coefficient being negative.

Market Power

Part of the foundation of the model is that banks derive market power from their deposit franchise, thus enabling them to impose a gap between the short-term and deposit rates. This in turn, according to the model, is a prerequisite for maturity transformation to be a process to hedge against risk rather than increasing it. Following Drechsler et al. (2017a) we therefore construct a Herfindahl-Hirschman index (HHI) to measure market concentration as a proxy for market power. The index is defined below:

$$HHI = \sum_{i=1}^{n} s_i^2 \tag{10}$$

where s is the market share in terms of deposits. We divide the bank branches into geographic areas by their zip codes. For each area separately, the deposits are summed to determine the market size. Similarly, for every bank we sum the total deposits in each area. Then we calculate the market share, in terms of deposits for the individual banks by their zip-code denoted branches. Finally the shares are squared and summed to get a measure of market concentration. To obtain a total yearly weighted average per bank we weight their bransch HHI by their respective deposit amount. We use data from the FDIC to obtain branch specific data.

Continuing the analysis we investigate the impact of market power on expense sensitivity in the first step. We regress the change in the interest expense on interest rate changes and market power in the following regression:

$$\Delta IntExp_{i,t} = \alpha_i + \phi HHI_{i,t} \sum_{\tau=0}^{3} (\beta_\tau^0 + \beta_\tau HHI_{i,t}) \Delta FFR_{\tau-t} + \varepsilon_{i,t} \tag{11}$$

where the recurring variables have been defined previously, $HHI_{i,t}$ is the Herfindahl-Hirschman index proxy of market power, and α_i is the individual fixed effect. We include both separate and interaction HHI variables. Summing the HHI and interest rate interaction variables yields a result of -0.079 and -0.094 respectively.. Both the negative sign as well as the quite substantial magnitude is indicative of relationship between market power and interest expense sensitivity. Compared to the results of Drechsler et al. (2017a), it suggests that the importance of market power may be even higher in the extended sample period.

The final step in this section is to examine the direct impact of market power on sensitivity matching. Analogously to previous steps, we use the regression above to calculate fitted values for the interest expense rate changes. Similarly, we perform a regression of interest income changes on the fitted expense rate changes while including Fed funds rate changes as control variables. We run the following regression.

$$\Delta IntExp_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_\tau \Delta FFR_{t-\tau} + \delta \Delta \widehat{IntExp_{i,t}} + \epsilon_{i,t} \tag{12}$$

In an alternative specification, consistent with the previous procedures, we include time fixed effects and exclude the federal funds rate. The results are depicted in Table 5, where the expense coefficient is 1.206 and 1.233 for the two specifications. We observe that the findings are close to the predictions of the model, which would be close to one, fitting the model predictions slightly better than in Drechsler et al. (2017a). The total sensitivity matching is also affected by the non-interest items on banks income sheets.

Overall the results are consistent with the findings of Drechsler et al. (2017a). There is no clear indication that the financial crisis has had a significant impact by only extending the time period. It may not be surprising considering the long sample period in most regressions. In addition, banks in the later years of the extended period may already start to recover and any impact diminish. This may lead to no or only a small net effect of adding additional years. In the next section we further investigate the impact of the low interest rate environment by performing additional tests to better assess the effects.

5.2 Extension

Sensitivity matching

In this section we repeat some of the previous regressions, but with a rolling window over shorter time periods. The series of estimates of the coefficients indicate whether the results are robust and hold over time and when, if any, structural breaks occur. Subsequently we investigate the impact of the protracted period of interest rates on banks' sensitivity matching. With their framework Drechsler et al. (2017a) provide a successive sequence of tests well suited as a basis for this analysis. By simply adding dummy variables we investigate the impact of the crisis on some of the previous regressions. By doing this we are able to observe the effect on the model predictions.

We perform rolling regressions that move one year per repetition, using the interest expense equation (7) with a window of four years from 1984 to 2014. We require that banks have fours years of observations. This is repeated for interest income changes and ROA. Thereafter, we take the cross-sectional winsorized average and the results are shown in Figure 7. Two features are striking. Firstly, it appears that the sensitivity matching of banks is a persistent phenomenon, especially in the two decades prior to the financial crisis. Interest and expense sensitivities largely follow one another. The resulting ROA exposure to the interest rate appear to be the difference between the two. There are some exceptions where there is a larger gap between the sensitivities, most noticeably around the crisis of 1987. Secondly, the matching is completely disrupted by the time of the financial crisis. ROA interest sensitivity jumps, increasing sharply and then reverses to a negative sensitivity. Interest income ambiguously drops to become negative and large in magnitude, while interest expense fluctuates at a somewhat lower level than prior to the crisis.

Initially, there appears to be other components of ROA that causes the sharp increase before the large negative drop, supposedly as a result of the large interest income sensitivity. The graph further suggests that the interest income and interest expense sensitivity converges. We observe what would be an increased net effect of the other items in ROA.

Bailey and Matyaš (2019) test for a structural break in the interest sensitivity of bank stock return and find that it occurs in late October 2008, this would correspond to the last quarter of 2008 in our data. Our method is not as precise, but it indicates a timing around 2008-2009. Interest income exhibits the most unambiguous change. They and Claessens et al. (2018) point out that it is the low interest rate that impact the relationship, and we observe a sharp decline in the Fed Funds rate around the same time (figure 1). In conjunction with our own observations from the rolling regression of the interest sensitivities we base further analysis that any structural break occurs around 2009.

Analogously to Bailey and Matyaš (2019), we add dummy variables to equation (7) to account for the change in the interest sensitivities and the relationship between them. We create interaction terms for each interest rate variable and include an intercept dummy as well.

$$\Delta IntExp_{i,t} = \alpha_i + \sum_{\tau=0}^{3} \beta_{1,i,\tau}^{Exp} \Delta FFR_{t-\tau} + \sum_{\tau=0}^{3} \beta_{2,i,\tau}^{Exp} \Delta FFR_{t-\tau} Dummy_t + \varepsilon_{i,t} \tag{13}$$

The dummy variables assume a value of zero before 2009 and one after the assumed break. Throughout the analysis, the dummy variables are defined in the same way. In each test we add dummy interaction terms. We calculate the average and winsorize the betas at the 5% level as in previous sections. The results in Table 6 show that the effect on the interest sensitivities appear to be much smaller in magnitude in contrast to the rolling regressions. The beta values prior to the crisis are largely consistent with those in Table 1. The sensitivity of ROA on the other hand increases sharply which can be observed in Table 6; from 0.054 to 0.794. However, it should be noted that the two methods are not entirely comparable since the regressions include different samples and averages the betas across different time periods.

Panel analysis

We reuse equation (8) and add the same set of dummy variables that we defined previously. As mentioned earlier this test puts more weight on banks with more observations. Therefore any banks that only appear a few periods in the data after the financial crisis will have less impact on the results. We run the regression defined below:

$$\Delta IntInc_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_\tau \Delta FFR_{t-\tau} Dummy_t + \delta \Delta \widehat{IntExp_{i,t}} Dummy_t + \phi Dummy_t + \epsilon_{i,t} \quad (14)$$

The sample includes the sample of all banks from 1984 that appears before and after the crisis and extends up to 2019. The result shows a much clearer picture, and one that the initial rolling analysis indicated; banks don't match their interest sensitivities to the same extent as before the crisis. The interaction term is -0.653 while the pre-crisis beta is similar to our previous results. From 2009 the sum of the coefficients is close to zero i.e. the sensitivities are not matched. The sample period also includes what could be a return to the pre-crisis interest rate sensitivity matching.

The impact on market power

We have established that there is an apparent break in the sensitivity matching. To examine whether this is related to the diminishing effect of market power on sensitivity matching, we proceed by adding dummy variables to the second stage regression to test the effects of the post-2008 low interest environment.

$$\Delta IntExp_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_\tau (\Delta FFR_{t-\tau}) Dummy_t + \delta \Delta \widehat{IntExp_{i,t}} Dummy_t + \phi Dummy_t + \epsilon_{i,t} \quad (15)$$

The results of the regression show that all of the explanatory value that market power offers in predicting the matching completely disappears after 2008. The dummy variable is almost as great in absolute value (-1.396) as the coefficient before the crisis rendering the total slightly negative (Table 8). In contrast, the interest rate control variables increase in magnitude. The overall picture is that banks fail to take advantage of their market power in a state of extremely low interest rates to lower the expense sensitivity to match the negative income sensitivity. In the model banks change their asset composition to match the level of interest expense sensitivity given by their deposit franchise. We find that the asset side is more unambiguously impacted by the crisis, with the interest sensitivity switching sign for a period of time. The implication is thus that banks cannot utilize their market power to match their interest income sensitivity with their interest expense sensitivity.

6 Conclusion

Our replication of Drechsler et al. (2017a) confirms their findings that banks engage in maturity transformation as a method to hedge interest risk. In our analysis, market power appears to have a larger impact on the expense interest sensitivity. Adding to and supporting their contribution, our results indicate that their findings seem to hold over time in shorter intervals before the onset of the financial crisis. Matching the interest sensitivities appears to be the a feature of the aggregate industry under non-extreme economic conditions. However, there are some indications that prior crises, such as the "Black Monday" crisis, had similar, although smaller, impact on banks' sensitivity matching. The resulting impact on ROA interest rate sensitivity was not as severe as under the financial crisis.

We demonstrate that within the framework of Drechsler et al. (2017a) crucial predictions of the model fail to hold in the low-interest period following the onset of the financial crisis. Banks apparent sensitivity matching abruptly ends around 2009. Both the sensitivities of income and ROA changes drastically and diverge. The former turns significantly negative while ROA sharply increases and the exhibits a large decline and turns negative. Interest expense sensitivity remains relatively stable. This indicates that there is a limit to the extent to which banks can use their market power to match their interest rate sensitivities.

Our results are similar to the findings Bailey and Matyaš (2019) in that banks' exposure to the interest rate changes significantly in the wake of the financial crisis. To our surprise it is the interest income sensitivity that is most affected by the crisis.

References

Bailey, M. and Matyas, J. (2019). What drives bank stock returns? an analysis using factor models. Master's thesis, Stockholm School of Economics.

Begenau, J., Piazzesi, M., and Schneider, M. (2015). Banks' risk exposures. Working Paper 21334, National Bureau of Economic Research.

Begenau, J. and Stafford, E. (2018). Do banks have an edge? *(Jan)*.

Bernanke, B. S. and Gertler, M. (1995). Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4):27–48.

Brunnermeier, M. K. and Koby, Y. (2018). The reversal interest rate. Working Paper 25406, National Bureau of Economic Research.

Claessens, S., Coleman, N., and Donnelly, M. (2018). "Low-For-Long" interest rates and banks' interest margins and profitability: Cross-country evidence. *Journal of Financial Intermediation*, 35A:1–16.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414.

Diamond, D. W. and Rajan, R. G. (2001). Liquidity risk, liquidity creation and financial fragility: A theory of banking. *Journal of Political Economy*, 109:287–327.

Drechsler, I., Savov, A., and Schnabl, P. (2017a). Banking on deposits: Maturity transformation without interest rate risk. Working Paper 24582, National Bureau of Economic Research.

Drechsler, I., Savov, A., and Schnabl, P. (2017b). The Deposits Channel of Monetary Policy*. *The Quarterly Journal of Economics*, 132(4):1819–1876.

Driscoll, J. C. and Judson, R. (2013). Sticky deposit rates. *Feds Working Paper*, 2013-80.

English, W. B., van den Huevel, S. J., and Zakrajsek, E. (2018). The reversal interest rate. *Journal of Monetary Economics*, 98:80–97.

Fama, E. F. (1985). What's different about banks? *Journal of Monetary Economics*, 15(1):29–39.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2):427–465.

Flannery, M. J. (1981). Market interest rates and commercial bank profitability: An empirical investigation. *The Journal of Finance*, 36(5):1085–1101.

Flannery, M. J. and James, C. M. (1984). The effect of interest rate changes on the common stock returns of financial institutions. *The Journal of Finance*, 39(4):1141–1153.

Gomez, M., Landier, A., Sraer, D., and Thesmar, D. (2020). Banks' exposure to interest rate risk and the transmission of monetary policy. *Journal of Monetary Economics*.

Hannan, T. and Berger, A. (1991). The rigidity of prices: Evidence from the banking industry. *American Economic Review*, 81(4):938–45.

Kashyap, A. K., Rajan, R., and Stein, J. C. (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of Finance*, 57(1):33–73.

Tella, S. D. and Kurlat, P. (2017). Why are banks exposed to monetary policy? Working Paper 24076, National Bureau of Economic Research.

Table 1: **Bank characteristics and interest rate sensitivity**

This table includes summary statistics on interest expense, income, and ROA betas. We also include a number of statistics which describe key bank characteristics. The sample in Panel A consists of all U.S. commercial banks from 1984 to 2019. The sample in Panel B is restricted to the largest 5% of banks by assets. Banks included in our sample have at least 20 quarterly observations.

Panel A: All banks

	All		Low beta	High beta
	Mean	St.Dev.	Mean	Mean
	(1)	(2)	(3)	(4)
Interest rate sensitivity				
Interest expense beta	0.361	(0.109)	0.276	0.446
Interest income beta	0.381	(0.167)	0.313	0.449
ROA beta	0.028	(0.332)	0.005	0.052
Bank characteristics				
Asset repricing maturity	3.601	(1.970)	3.815	3.310
Liabilities repricing maturity	0.432	(0.256)	0.445	0.413
Log assets	4.927	(0.611)	4.825	5.055
Loans/Assets	0.582	(0.162)	0.564	0.604
Securities/Assets	0.268	(0.157)	0.270	0.244
Core Deposits/Assets	0.734	(0.126)	0.752	0.712
Equity/Assets	0.103	(0.058)	0.109	0.096
Observations	15,361		7680	7681

Panel B: Top 5%

	All		Low beta	High beta
	Mean	St.Dev.	Mean	Mean
	(1)	(2)	(3)	(4)
Interest rate sensitivity				
Interest expense beta	0.431	(0.122)	0.332	0.531
Interest income beta	0.439	(0.184)	0.346	0.532
ROA beta	0.050	(0.318)	0.057	0.043
Bank characteristics				
Asset repricing maturity	4.024	(2.188)	4.335	3.484
Liabilities repricing maturity	0.374	(0.366)	0.371	0.379
Log assets	6.343	(0.759)	6.196	6.526
Loans/Assets	0.633	(0.154)	0.630	0.636
Securities/Assets	0.211	(0.135)	0.231	0.186
Core Deposits/Assets	0.633	(0.195)	0.685	0.570
Equity/Assets	0.095	(0.066)	0.098	0.091
Observations	768		384	384

Table 2: **Interest sensitivity matching**

This table shows the results of the two-stage OLS regressions to estimate interest sensitivity matching using interest income as the dependent variable in the panel regression. The even columns contain the coefficient estimates and the uneven columns contain standard errors. The sample covers banks with at least 5 years of observations from 1984 to 2019.

$$\Delta IntExp_{i,t} = \alpha_i + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta FFR_{t-\tau} + \epsilon_{i,t} \qquad \text{[Stage 1]}$$

$$\Delta IntInc_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_{i,\tau} \Delta FFR_{t-\tau} + \delta \Delta \widehat{IntExp_{i,t}} + \epsilon_{i,t} \qquad \text{[Stage 2]}$$

	All banks		Top 10%		Top 5%		Top 1%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \widehat{IntExp}$	0.728***	0.726***	1.369***	1.366***	1.373***	1.369***	1.418***	1.415***
	(0.215)	(0.215)	(0.095)	(0.096)	(0.114)	(0.115)	(0.094)	(0.099)
$\sum \gamma_\tau$	0.103		-0.148		-0.169		-0.245	
	(0.119)		(0.119)		(0.130)		(0.135)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	1,205,868	1,205,868	126,692	126,692	62,068	62,068	12,774	12,774
Bank clusters	15,361	15,361	1,536	1,536	768	768	153	153
Time clusters	142	142	142	142	142	142	142	142
R^2	0.005	0.002	0.080	0.051	0.090	0.062	0.102	0.073

Table 3: **Asset duration and expense betas**

This provides the results of the OLS regression estimation of repricing maturity on expense interest rate sensitivity. Repricing maturity is the proxy for duration. The interest rate sensitivity is the 5% winsorized sum of the beta coefficients estimated with regression (7). Column (1) includes the coefficients of all banks while column (3) only includes the top 5% by assets. The even columns contain the respective standard errors. The standard errors are double-clustered by quarter and bank. The sample covers banks from with at least 5 years of observations 1997-2019.

	Repricing maturity			
	All banks		Top 5%	
	(1)	(2)	(3)	(4)
Interest expense beta	-3.028***	-3.829***	-3.278**	-3.681**
	(0.229)	(0.243)	(1.156)	(1.261)
Wholesale funding ratio		-0.798***		-0.910
		(0.211)		(0.990)
Equity ratio		-1.415***		-5.381***
		(0.430)		(1.477)
log Assets		0.512***		0.410**
		(0.039)		(0.143)
Time FE	Yes	Yes	Yes	Yes
Obs.	609,557	606,716	27,777	25,676
Bank clusters	10,841	10,839	522	520
Time clusters	90	90	90	90
R^2	0.018	0.040	0.025	0.053

Table 4: **Securities share and expense betas**

This provides the estimates of the relationship between security share and expense interest rate sensitivity resulting from the two OLS regressions.. Repricing maturity is the proxy for duration.The interest rate sensitivity is the 5% winsorized sum of the beta coefficients estimated with regression (7). Column (1) includes the coefficients of all banks while column (3) only includes the top 5% by assets. The even columns contain the respective standard errors. The standard errors are double-clustered by quarter and bank. The sample covers banks from with at least 5 years of observations 1997-2019.

	Securities/Assets			
	All banks		Top 5%	
	(1)	(2)	(3)	(4)
Interest expense beta	-0.248***	-0.187***	-0.130*	-0.132*
	(0.017)	(0.019)	(0.060)	(0.061)
Wholesale funding ratio		-0.162***		0.049
		(0.018)		(0.064)
Equity ratio		0.047		-0.400***
		(0.032)		(0.094)
log Assets		-0.010***		-0.014$^{\cdot}$
		(0.003)		(0.007)
Time FE	Yes	Yes	Yes	Yes
Obs.	610,705	607,821	28,994	26,893
Bank clusters	10,855	10,853	541	539
Time clusters	90	90	90	90
R^2	0.023	0.034	0.011	0.050

Table 5: **Market power and interest sensitivity matching**

This table contains the results of the OLS regressions estimating the relationship between market power (HHI) and the matching of interest rate sensitivities. The sample contains data from 1994 to 2019.

$$\Delta IntExp_{i,t} = \alpha_i + \phi X_{i,t} + \sum_{\tau=0}^{3}(\beta_\tau^0 + \beta_\tau X_{i,t})\Delta FFR_{t-\tau} + \epsilon_{i,t} \qquad \text{[Stage 1]}$$

$$\Delta IntInc_{i,t} = \lambda_i + \sum_{\tau=0}^{3}\gamma_\tau \Delta FFR_{t-\tau} + \delta\Delta\widehat{IntExp_{i,t}} + \epsilon_{i,t} \qquad \text{[Stage 2]}$$

	Market concentration (zip code)	
	(1)	(2)
Stage 1:		
$\sum \beta_\tau$	-0.079	-0.094
β_0	-0.059**	-0.060***
	(0.020)	(0.015)
β_1	-0.050**	-0.055***
	(0.018)	(0.014)
β_2	0.006	-0.000
	(0.021)	(0.017)
β_3	0.024	-0.022
	(0.019)	(0.018)
R^2	0.192	0.002
Stage 2:		
$\Delta\widehat{IntExp}$	1.206***	1.229***
	(0.174)	(0.162)
$\sum \gamma_\tau$	-0.036	
	(0.138)	
Bank FE	Yes	Yes
Time FE	No	Yes
R^2	0.040	0.001
Obs.	726,121	726,121
Bank clusters	12,613	12,613
Time clusters	102	102

Table 6: **Cross-sectional dummy test**

Here we test for the impact of the financial crisis by running regressions for banks' interest expense, income, and ROA betas with included dummy variables to capture time-period dependant effects. Column (1) represents the resulting slope coefficients of betas and column (2) represents the resulting slope coefficients of the dummy interaction terms. The regressions are specified analogously to equation (13).

	Beta (1)	Dummy (2)
Interest expense	0.334	0.073
	(0.086)	(0.358)
Interest income	0.355	-0.006
	(0.135)	(0.850)
ROA	0.053	0.794
	(0.256)	(5.056)
Observations	15,361	

Table 7: **Panel regression dummy test**

Here we test for the impact of the financial crisis on banks' ability to match their interest expense and interest income betas. This is done by running an OLS panel regression as specified in equation (8), but with included dummy variables to capture any differences between our specified time-periods (before and after 2008). Column (1) shows the resulting slope coefficient and (2) represents the slope coefficient of the dummy interaction terms.

$$\Delta IntInc_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_\tau \Delta FFR_{t-\tau} Dummy_t + \delta \Delta \widehat{IntExp_{i,t}} Dummy_t + \phi Dummy_t + \epsilon_{i,t}$$

	Coefficient estimate (1)	Dummy (2)
$\Delta\widehat{IntExp}$	0.736***	-0.653**
	(0.219)	(0.213)
$\sum \gamma_\tau$	0.102	0.326
	(0.122)	(0.374)
Bank FE	Yes	Yes
Time FE	No	No
Obs.	1,205,868	1,205,868
Bank clusters	15,361	15,361
Time clusters	142	142
R^2	0.005	0.005

Table 8: **Market power dummy test**

Here we test for the impact of the financial crisis on the relationship between market power and banks' interest rate sensitivity matching. The regression is specified below, and includes dummy variables to capture the differences between the specified time-periods before and after 2008. Column (1) shows the resulting slope coefficients and column (2) represents the the resulting slope coefficient of the dummy interaction terms.

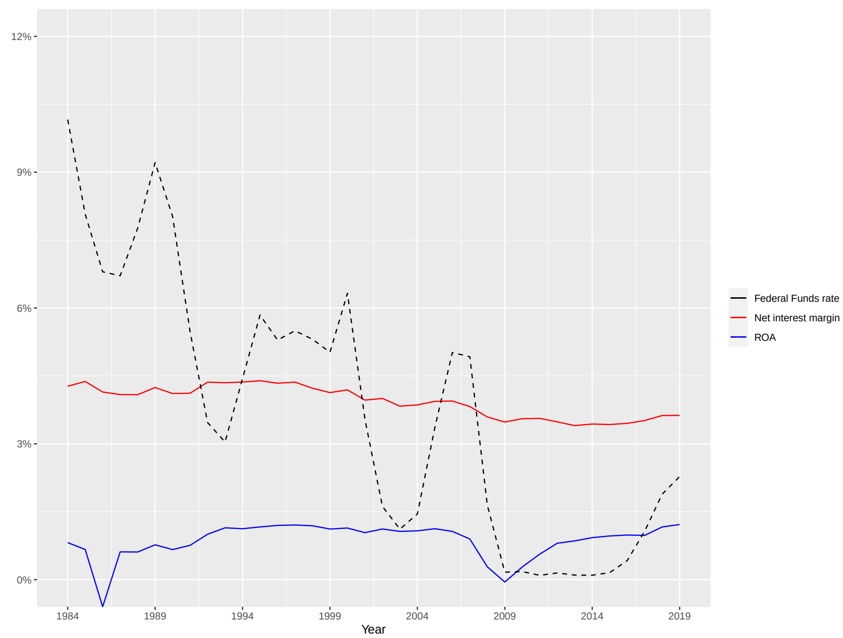
$$\Delta IntExp_{i,t} = \lambda_i + \sum_{\tau=0}^{3} \gamma_\tau (\Delta FFR_{t-\tau}) Dummy_t + \delta \Delta \widehat{IntExp_{i,t}} Dummy_t + \phi Dummy_t + \epsilon_{i,t}$$

	Coefficient estimate (1)	Dummy (2)
$\Delta\widehat{IntExp}$	1.345***	-1.396***
	(0.175)	(0.234)
$\sum \gamma_\tau$	-0.067	0.531
	(0.152)	(0.386)
Bank FE	Yes	Yes
Time FE	No	No
Obs.	726,121	726,121
Bank clusters	12,613	12,613
Time clusters	102	102
R^2	0.042	0.042

Figure 1: **Time series of NIM, ROA, and interest rates**

The figures below show a plotted time series of net interest margin and return on assets (Panel A), and interest income and expense rates (Panel B). The plotted values are calculated as mean values from all banks in our dataset, and cover the timeframe of 1984 to 2019. The FFR rate is also included in both panels for reference.

Panel A: Federal funds rate, NIM, and ROA



Panel B: Federal funds rate and interest expense rates

Figure 2: **Repricing maturity of assets and liabilities**

In this figure we plot the repricing maturity of bank assets and liabilities. The values are calculated as mean values for the aggregate bank sector in the U.S. (our complete dataset and cover the timeframe of 1997 to 2019. The estimation of repricing maturities is described in further detail in Appendix A.

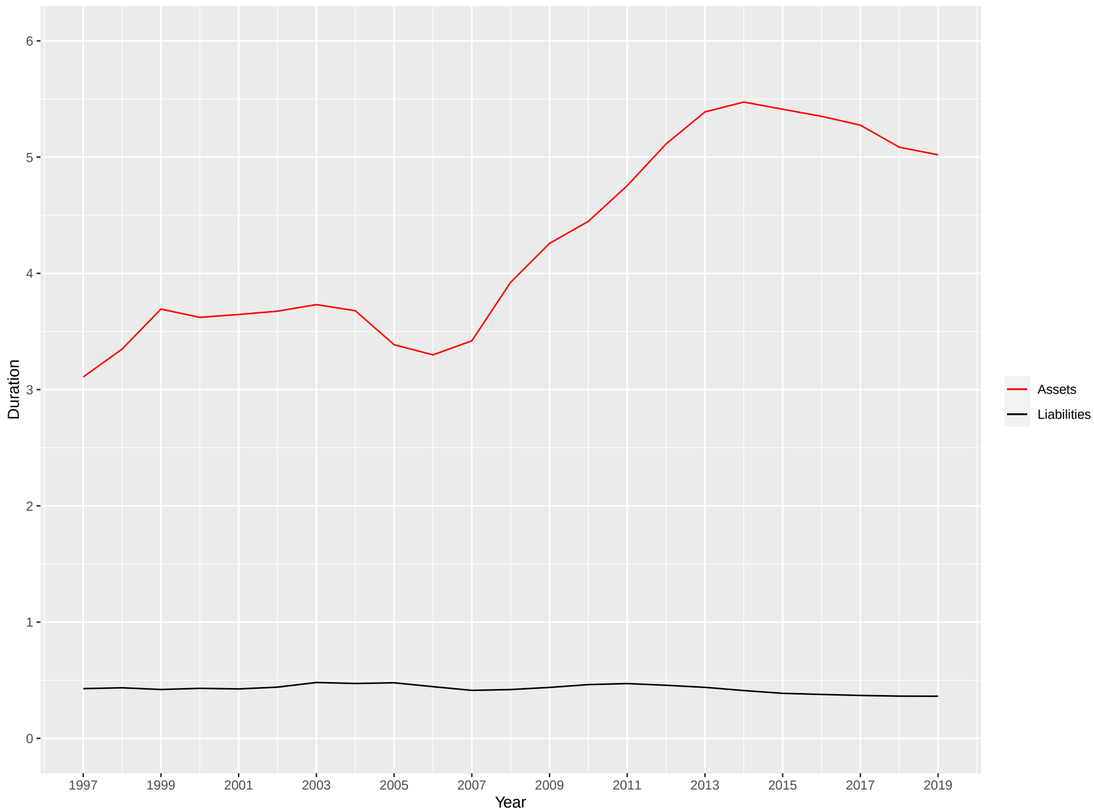
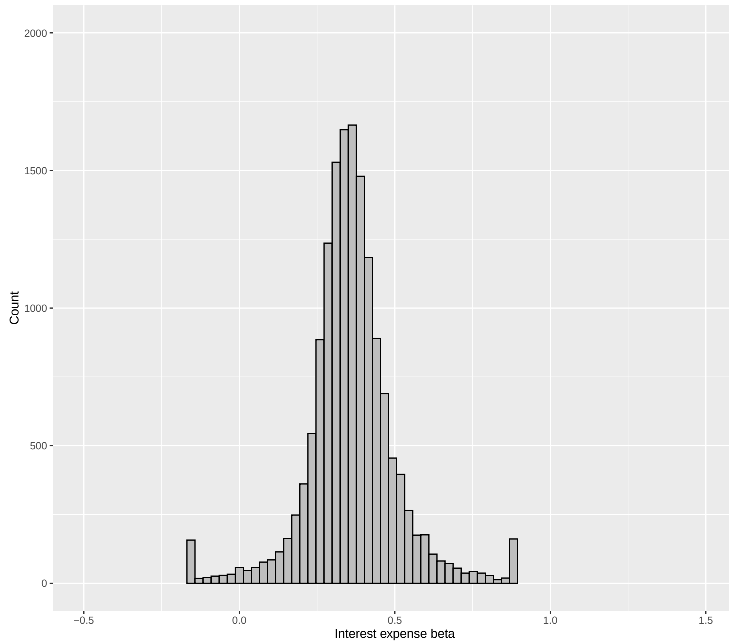


Figure 3: **Interest expense and interest income beta distribution**

The figures below provide a visualisation of the distribution of calculated interest expense and interest income betas for banks in our sample. Filtering is done by requiring banks to have at least 20 quarterly observations during our selected timeframe (1984-2019). The calculated betas are winsorized at 1%

Panel A: Distribution of interest expense betas



Panel B: Distribution of interest income betas

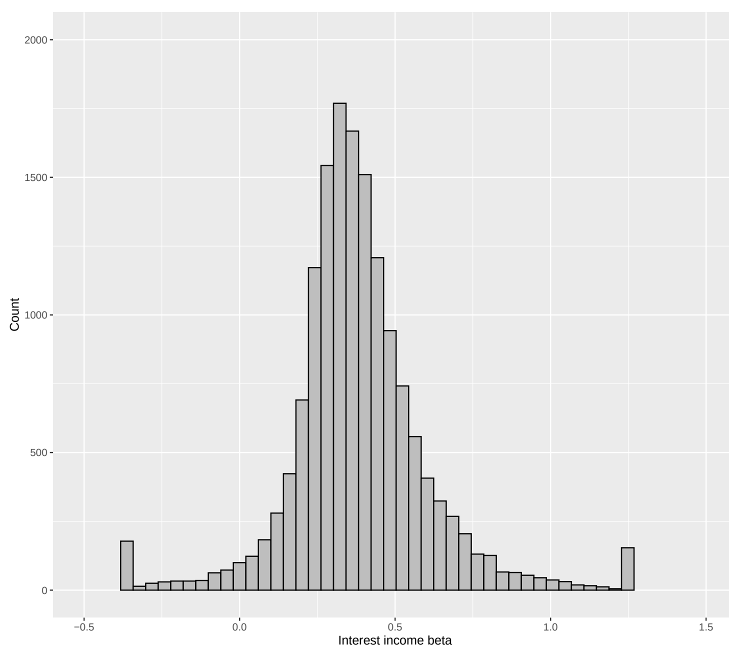
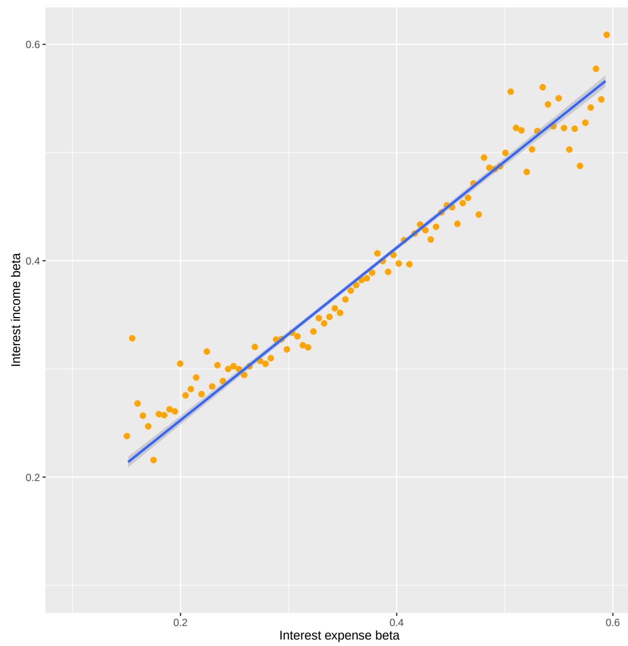


Figure 4: **Interest expense, interest income, and ROA matching**

The figures below are constructed as bin scatter plots of interest income and interest expense betas (Panel A), ROA betas and interest expense betas (Panel B). The sample consists of all banks in our filtered sample that have at least 20 quarterly observations. The betas are winsorized at 5%, and banks are grouped into 100 bins by their interest expense beta. The sample covers the timeframe 1984-2019.

Panel A: Matching between interest income betas and interest expense betas



Panel B: Matching between ROA betas and interest expense betas

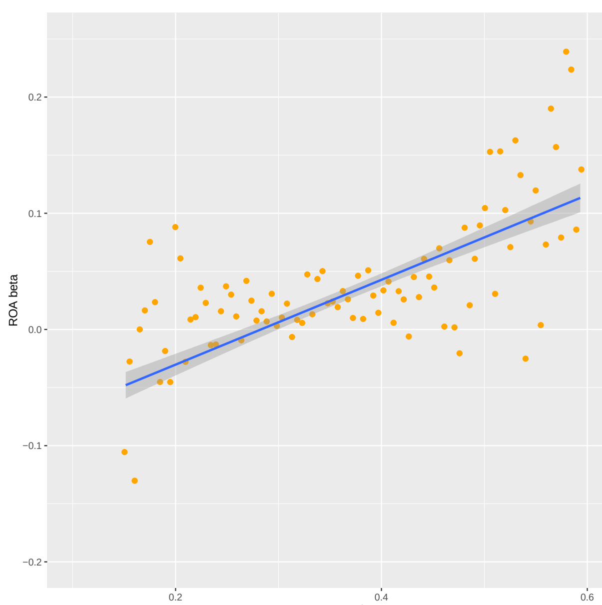


Figure 5: **Interest expense betas and asset duration (2019)**

The figure below is constructed as a binned scatter plot of banks' repricing maturity against their interest expense betas. Repricing maturities are calculated as described in Appendix A. The sample covers 1997 to 2019, and is filtered for banks that have at least 20 quarterly observations. The interest expense betas which are used to group the banks into 100 bins, are winsorized at the 5% level.

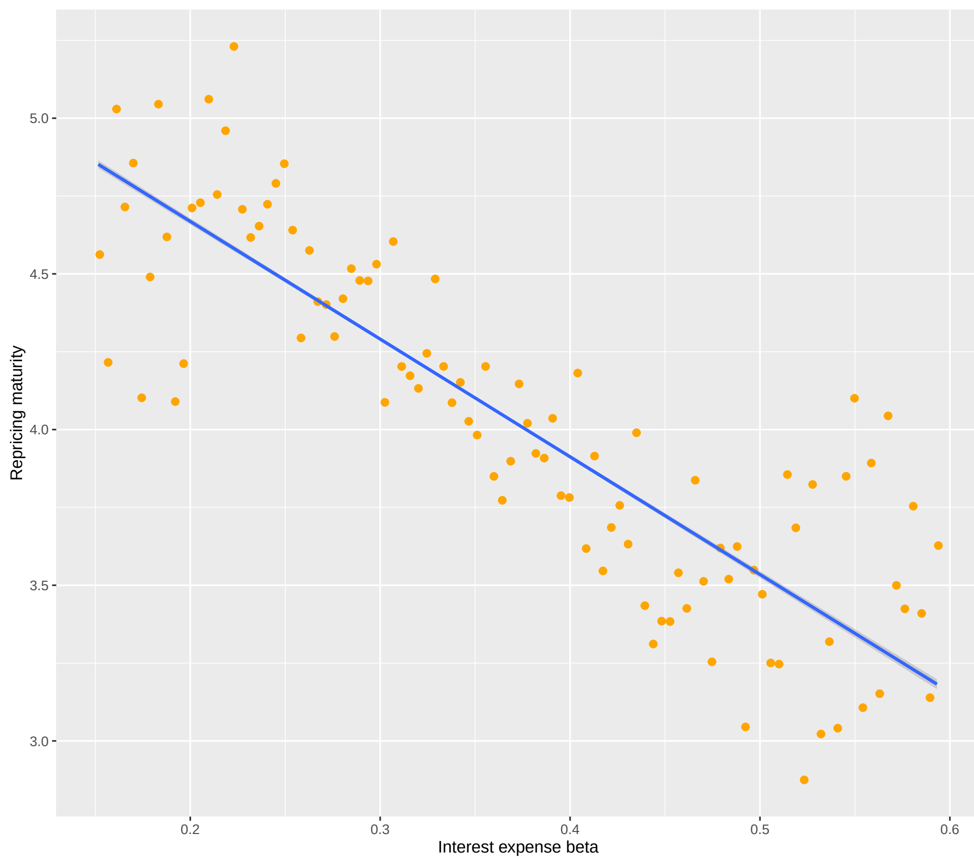


Figure 6: **Interest expense betas and market concentration (2019)**

The figure below is constructed by plotting banks' interest expense betas against their calculated HHI-index. Banks are grouped into 100 bins by their HHI-index, and then the average interest expense beta within each bin is plotted. The sample covers the timeframe of 1994-2019, and contains banks with at least 20 quarterly observations.

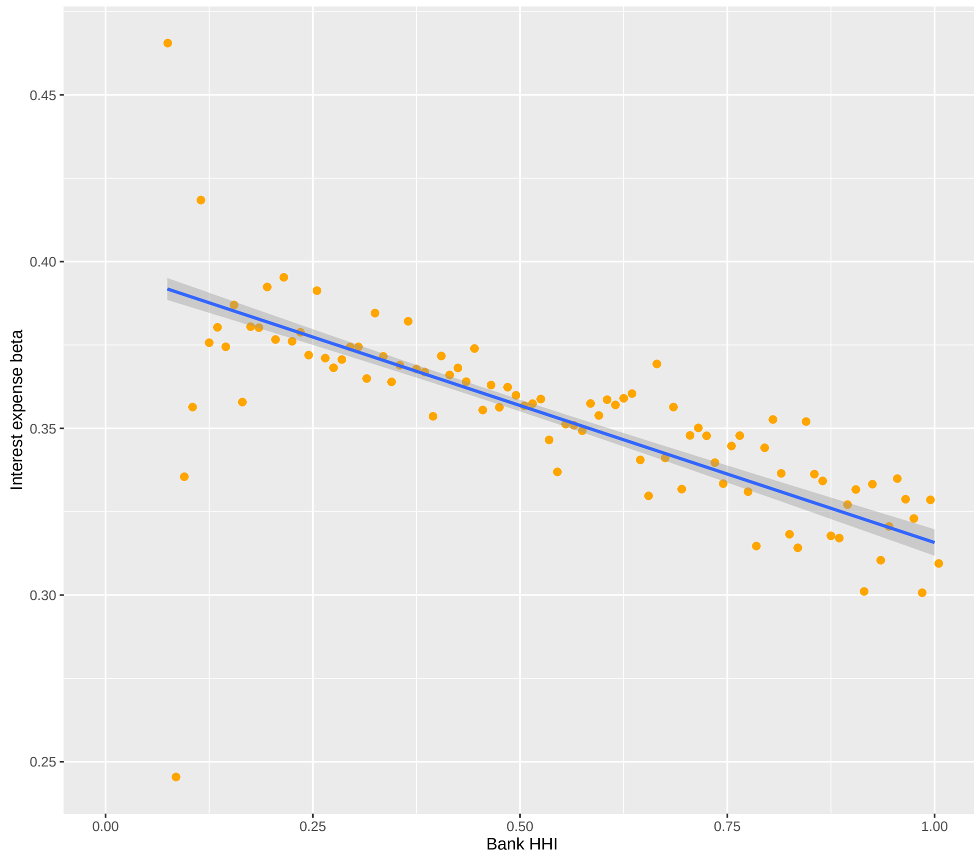
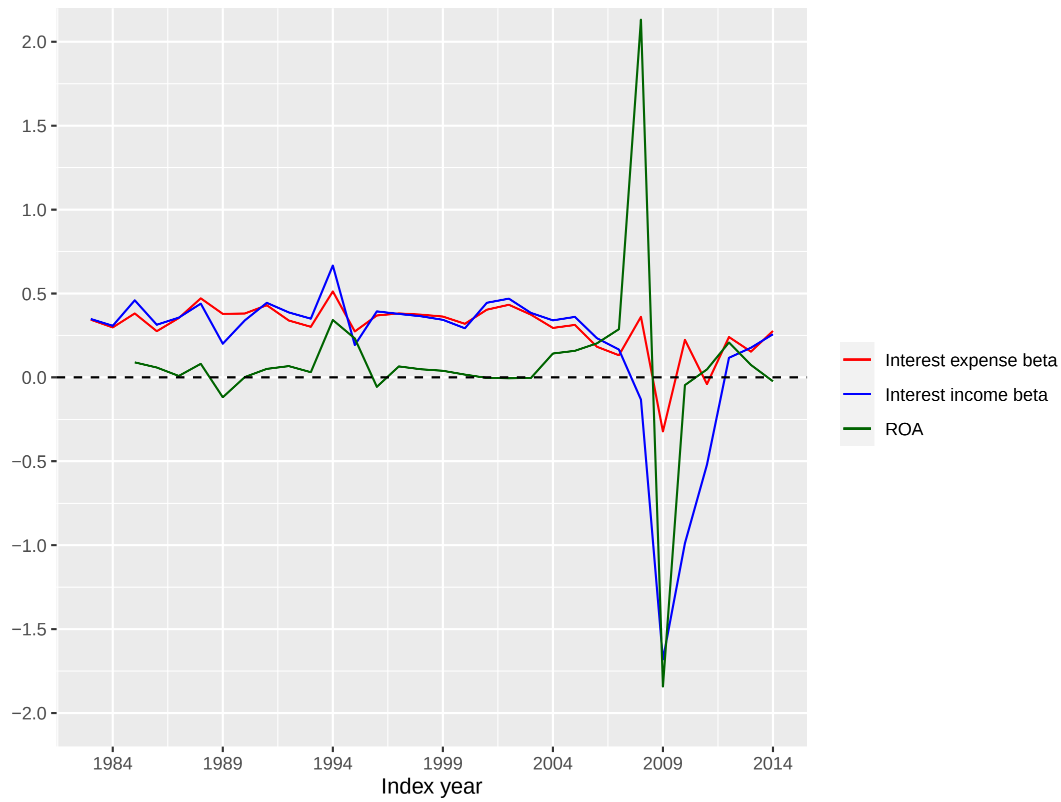


Figure 7: **Time series of rolling regressions**

The figure illustrates our results when running a rolling regression for the interest expense betas, interest income betas, and ROA betas. The window width for the rolling regression is specified as 4 years. Index year corresponds to the first year in a given window.



Appendix

A Calculating repricing maturities

We use the same proxy for duration (repricing maturity) as Drechsler et al (2017a). The repricing maturity of a liability or asset is determined by the time until whichever comes first of the maturity or the reset of the rate, determined by the prevailing rates.

Following Drechsler et al. (2017a), we apply the same methodology as English et al. (2012). In their reports to the FDIC banks classify their assets in five categories: residential mortgage loans, all other loans, treasuries and agency debt, MBS secured by residential mortgages and all other MBS. Each category is grouped into six bins with different intervals of repricing maturity: 0-3 months, 3-12 months, 1-3 years, 3-5 years, 5-15 years and over 15 years, respectively.

For each bin the mid-point is assumed to represent the average repricing maturity, e.g. we assign a value of 2 years for the 1-3 years bin. The last bin is given a midpoint of 20 years. An entire asset category's repricing maturity is calculated by taking the weighted average of each bin, where the recorded balance sheet value is the weight. Finally, to estimate the repricing maturity of all assets we similarly calculate the weighted average. In some cases, cash and fed funds sold are added with a repricing maturity of zero.

The repricing maturity of the liability categories and liabilities in their entirety are calculated similarly to the assets. Small and large time deposits are divided into four bins, with the following intervals: 0-3 months, 3-12 months, 1-3 years and over 3 years. They are assigned their respective mid-points as maturities and the last been 5 years.(including savings and transaction deposits) are their corresponding mid-points, with the last bin at 5 years. Starting in 2017 the cut-off point between small and large time deposits changes, but since we are only interested in the sum total it has no impact on the continuity of the data. Demandable deposits are assigned a value of zero, as is wholesale funding (e.g. fed funds purchased and repo) as they constitute short-term liabilities. Finally, subordinate debt is assumed to have a maturity of 5 years

B Filtering

We filter out a few extreme observations that skew some of the results. Over the entire sample we require banks to have at least 20 observations in the Call Reports data. For some tests we have additional minimum observational requirements, stated in the respective tables. The resulting sub-samples are generally similar. Observations with between zero and one thousand dollars in assets are excluded as well as some few observations where some income measures are negative (interest income, non-interest income) , which would otherwise result in extreme ratio measures. In combination with the requirement that banks have at least 20 quarterly observations this excludes some banks entirely amounting to some additional tens of banks.