BANKS' ECONOMIC RISK EXPOSURES IN A LOW INTEREST RATE ENVIRONMENT

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Abstract:

This paper studies banks' economic risk exposures over time using daily frequency data. We find that the theoretical risk factors banks are exposed to, credit risk and interest rate risk, are alone unsuccessful in explaining variation in bank equity returns. We confirm that banks' interest rate exposure has reversed in the low interest rate environment after the financial crisis. By examining the attributes of banks with the largest negative reaction to decreases in interest rates after the financial crisis, our results indicate that large, profitable, deposit-reliant banks are main contributors to this reversal.

Keywords:

Credit risk, interest rate exposure, low interest rates, bank profitability, factor models

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1 Introduction

Economic policy decisions need to be substantiated with knowledge of banks' exposure to macroeconomic risks. Traditionally, banks engage in the business of maturity transformation as they take short-term deposits and originate longer-term loans. According to conventional wisdom, this exposes them to interest rate risk and credit risk. This conventional knowledge has been confirmed empirically (see Begenau et al., 2015) and bank equity returns have been found to decrease following an increase in the level of interest rates (Flannery & James, 1984, English et al., 2018). However, the relationship between interest rates and bank returns is ambiguous. A decrease in long-term interest rates often implies a flattening of the yield curve, which should negatively affect banks' net interest margins. Nevertheless, this decrease will also result in capital gains on long-term assets. A decrease in short-term interest rates has also been found to dually impact banks' credit risk by increasing bank risk taking but simultaneously reducing credit risk on outstanding loans (European Central Bank, 2007).

In the aftermath of the financial crisis, the relationship between banks' returns and economic risk factors has become increasingly complex. With long-term rates at historically low levels and short-term rates near zero, banks' equity returns have gone from being positively affected by decreases in interest rates to being negatively affected (see Chakbazof & Sviberg, 2020, Bailey & Matyáš, 2019, Ampudia & Van den Heuvel, 2018). This can be linked to banks' reluctance to pay negative rates on retail deposits, since cash with its zero nominal yield then would be a better option for depositors. This zero lower bound on deposits can therefore lead to a similar effect as a flattening of the yield curve when interest rates decline, as banks' interest income decreases along with rates, but interest costs adjust only partially (Ampudia & Van den Heuvel, 2018). Additionally, when rates eventually begin to rise after a low-for-long environment, credit risk is also expected to increase (European Central Bank, 2007).

This recent, more complex economic environment calls for an updated understanding of banks' economic risk exposures. This paper examines the link between bank equity values and their economic risk factors over time and how it varies with different bank attributes. Our contribution is twofold. Primarily, we determine if the findings by Bailey & Matyáš (2019) are replicable using data on a daily frequency as opposed to the monthly data used in their study. Specifically, we address the question of how well credit and interest rate risk can explain bank equity returns and if banks' interest rate sensitivity has changed over time. Testing their findings with higher-frequency data is important as it might reveal different results in regards to the factor loadings, model fit and statistical significance of the results.

Second, we group banks by their interest rate sensitivity after the financial crisis to determine differences in attributes between them. This allows us to draw conclusions regarding what might be driving the shift in interest rate sensitivity for the banking industry. We investigate differences in nine different attributes chosen with the preconception that they can impact interest rate risk exposure. These include; deposit ratio, bank size, book-to-market ratio, loans-to-deposit ratio, loans-to-assets ratio, maturity gap, income gap, net profit margin, and derivatives ratio. We hypothesize that deposit reliant banks should be more negatively affected by decreases in interest rates in the post crisis environment, linking it to the compressed net interest margins caused by low interest rates as argued by Ampudia & Van den Heuvel (2018). We test this hypothesis further by also creating sorted portfolios based on deposit reliance.

Our results confirm the findings by Bailey & Matyáš (2019) that credit and interest rate risk do not successfully explain variation in bank stock returns. Likewise, we confirm that prior to the financial crisis, bank stock returns were positively impacted by decreases in interest rates, but that in the low-rate environment after the financial crisis this relationship has reversed. Surprisingly, we also find that banks are more sensitive to both the level and slope of the yield curve in the 2016-19 period, compared to the previous period 2010-15 which had lower interest rates.

We find indications that large, profitable, deposit-reliant banks are driving the reversal of interest rate sensitivity after the financial crisis. Additionally, we find evidence that banks with lower book-to-market ratios, lower loans-to-deposit ratios, higher income gaps, and higher derivatives ratios are also contributors to the reversal.

Our findings are important for a number of reasons. Given banks' importance to a well-functioning economy, it is important for regulators to understand the implications of monetary policy on their performance. This is especially important in the recent economic environment with historically low rates, as previous knowledge may no longer be valid under these extraordinary circumstances. Additionally, our findings are relevant to equity investors, as they shed new light on banks' risk exposures in the current economic environment.

For our study, we construct three economic risk factors measuring interest rate risk, credit risk, and risk associated with the slope of the yield curve. The interest rate risk factor is the daily return on a portfolio of 5-year US treasury bonds. The credit risk factor is the residuals from regressing daily excess returns of a portfolio of BBB corporate bonds on our interest rate factor. Finally, the slope factor is given by the daily change in the spread between the yield on 10-year and 1-year maturity treasuries.

Subsequently, we create factor models and regress the excess return of a market capitalization-weighted portfolio of bank stocks to obtain risk factor sensitivities over time. Second, we run a factor model on each individual bank in our sample and group them according to their post-crisis interest rate sensitivity. We then obtain summary statistics of our nine attributes for each of the groups, in order to uncover possible drivers of the reversal of interest rate sensitivity. Finally, we further investigate if deposit reliance can be a main driver by creating sorted portfolios based on this variable.

This paper is structured as follows. Section 2 discusses the related literature; Section 3 presents the methodological approach; Section 4 contains the results of our empirical analysis; Section 5 concludes.

2 Literature Review

Evidence has been found by several researchers that banks' returns are affected by interest rates, either in the form of the level or the slope of the yield curve (see Flannery & James, 1984, Viale et al., 2009, English et al., 2018). Begenau et al. (2015) exploit a two-factor model including credit and interest rate risk to investigate the risk exposures of individual positions on bank's balance sheets. They find that these two factors are able to explain ca. 50-90% of asset returns. Following this paper, Bailey & Matyáš (2019) conclude that these two factors are only able to explain ca. 7-50% of bank equity returns using monthly data. Moreover, they find that banks' sensitivity to the level and slope of the yield curve has shifted since the financial crisis, which is unique for the banking industry. We extend the paper by Bailey & Matyáš in two main dimensions. First, we use daily data to further examine the explanatory power of the interest rate and credit risk factors on bank equity returns, as well as their loadings over time. Second, we investigate the reversal in interest rate sensitivity further by determining if sensitivities differ depending on certain bank attributes.

A shift in banks' exposure to interest rate risk following the financial crisis has been documented by other authors too. On a sample of European banks, Ampudia & Van den Heuvel (2018) find that with rates close to or below zero after the financial crisis, further unexpected interest rate cuts became detrimental for banks' equity values. Moreover, they find an increased interest rate sensitivity for banks that rely heavily on deposit funding, which they explain as a consequence of banks' reluctance to pay negative rates on deposits. In an extension of the paper by English et al. (2018), Chakbazof & Sviberg (2020) similarly conclude that the reaction of banks' stock returns to unexpected decreases in interest rates and the slope of the yield curve has reversed, from positive to negative, after the financial crisis. Our study differs from Ampudia & Van den Heuvel and Chakbazof & Sviberg mainly in methodology. While these authors conduct event studies to assess the effect of surprise interest rate changes on bank equity values, we are evaluating the asset pricing models as proposed by Begenau et al. (2015) and Bailey & Matyáš (2019). Furthermore, our paper has an increased focus on uncovering drivers in the observed reversal in banks' interest rate sensitivity after the financial crisis.

Our paper also relates to the study by Brunnermeier & Koby (2018) who propose the notion of a "reversal interest rate", where accommodative monetary policy reverses its intended effect and becomes contractionary for lending under certain conditions. Similar to these authors, we investigate the effects of low interest rates on banks. However, we differ from their paper both in methodology and scope; instead of calibrating an economic model, we empirically test banks' economic risk exposures over time and determine if sensitivities depend on certain bank attributes.

3 Methodological Approach

In this section, we first present the data used in our study. Second, we describe the methodology used to determine the link between bank equity returns and their economic risk factors. Third, we describe our methodology to analyze if banks' interest rate sensitivity after the financial crisis depends on certain bank attributes.

3.1 Data

The sample period underlying our analysis is January 1st, 1980, to December 31st, 2019. This time period is chosen to provide an extensive overview of changes in the relationship between bank returns and interest rate risk over time. Some of the data used does not date back to the start of our sample, in that case a shorter time period is opted for.

In our sample, banks are defined as all firms with a Standard Industrial Classification (SIC) code that begins with 60, which are depository institutions. Non-depository institutions such as insurance companies, pension funds, finance companies etc. are excluded as interest lies with banks conducting traditional banking activities[1]. Note that the presented definition of banks includes firms defined as bank holding companies otherwise known to have a historical SIC code of 6712. We follow the method suggested by Kenneth French on his website, and thus prioritize SIC codes from Compustat Bank

[1] Our definition of traditional banking activities include the business of maturity transformation, where banks originate long-term loans and finance them mainly through short-term deposits.

Fundamentals Annual before those of Compustat Fundamental Annual and CRSP when constructing our bank dataset.

We gather daily bank stock data and other trading information from the Center for Research in Security Prices (CRSP). Per common practice in the asset pricing literature, our dataset is restricted to only include ordinary common shares on the three major US stock exchanges NYSE, NASDAQ, and AMEX.

Accounting information is retrieved from Compustat Fundamentals Quarterly and from the Bank Holding Company section of the Bank Regulatory database, the latter from which we obtain call report data. The first call reports are available from 1986. Additionally, we obtain some financial measures from the Financial Ratios Suite supplied by WRDS.

To construct our interest rate risk factor, we retrieve returns on a portfolio of treasury bonds with 5-year maturity from CRSP Treasuries Fixed Term Indexes. We also obtain daily treasury yield curve rates of 1- and 10-year maturities for the slope factor from the Federal Reserve Bank[2]. To use when constructing our credit risk factor, we obtain the ICE BofA BBB US Corporate Index Total Return Index Value from the Federal Reserve Bank of St. Louis (FRED) database, where daily returns are available from 1988 and onwards.

Finally, we retrieve the risk-free rate, measured by the daily return on 30-day treasury bills, from the Fama French Portfolios and Factors database. From this database, daily market excess returns are also collected.

To clean our dataset from extreme outliers, we remove the most extreme observations (1st and 99th percentile) from our sample in regards to equity returns and the reported attributes[3]. This is done to ensure that data is representative of healthy banks with normal banking activities and that results are not driven by extreme observations in our sample.

3.2 Banks' Economic Risk Exposures

We create factor models using simple measures of credit and interest rate risk to understand how these can explain variation in bank equity returns and to replicate the study by Bailey & Matyáš (2019). While conducting event studies in regards to interest rate risk is common in recent literature (see English et al., 2018, Chakbazof & Sviberg,

[2] To use for robustness checks, we also retrieve daily returns of Treasury bond portfolios with maturities of 1 and 10 years. For the same purpose, we also retrieve daily Treasury yield curve rates of 5-year maturities.

[3] We do not remove the 99th percentile of total assets nor the 1st percentile of derivatives ratio.

2020, Ampudia & Van den Heuvel, 2018), this is not the objective of our study. We reduce omitted variables problems by controlling for the market factor in our regressions. However, this may give rise to simultaneity problems causing bias in our estimates. Nevertheless, our results are in line with those who have used event studies to reduce both these issues. Finally, our study has less emphasis on determining an exact coefficient estimate for interest rate risk, but instead to understand changes in patterns and the underlying reasons for them.

To address the relationship between banks' equity returns and interest rate and credit risk, we begin by creating a market capitalization-weighted portfolio of the bank stocks in our sample. We use portfolios instead of individual stocks to diversify the idiosyncratic risk possessed by individual firms. This allows for more accurate beta estimates in our time series regressions. Additionally, it is suitable as stated by Ang et al. (2020), as we in our initial regressions are more interested in understanding the risk exposures for the banking industry as a whole, than understanding what happens in the cross-section between individual banks.

As our paper in part aims to validate the findings of Bailey & Matyáš (2019), our method is to a large extent similar to theirs. However, in contrast to their use of monthly data, we use daily data on equity returns as well as in the construction of our risk factors. As a first step in our study, we construct an interest rate risk and credit risk factor as done by Bailey & Matyáš (2019) following the model used by Begenau et al. (2015). The interest rate risk factor is proxied by the daily return on a portfolio of risk-free 5-year US treasury bonds. The credit risk factor is obtained by taking the residuals from regressing the daily excess returns of the portfolio of BBB corporate bonds on our interest rate factor. This isolates the credit risk in the BBB corporate bonds and makes the two factors orthogonal to each other.

The initial baseline regression we run is given in equation (1a). This equation is identical to the one done by Bailey & Matyáš (2019), as an extension of the model by Begenau et al. (2015). This equation mainly allows us to assess how well the two economic risk factors can explain banks' equity returns, but it also allows us to find patterns on how banks' exposure to them has changed over time.

$$(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot Level(5Y)_t + \beta_2 \cdot CreditRisk_t + \epsilon_t \tag{1a}$$

where $(r_{p,t} - rf_t)$ is the daily excess return on the constructed bank portfolio. $Level(5Y)_t$ is the daily interest rate risk factor and $CreditRisk_t$ is the daily credit risk factor.

We proceed by adding the market factor to our regression as a control. This equation is given in (1b).

$$(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - rf)_t + \beta_2 \cdot Level(5Y)_t + \beta_3 \cdot CreditRisk_t + \epsilon_t \tag{1b}$$

where $(Mkt - rf)_t$ is the daily market excess return.

Following Bailey & Matyáš (2019), we further investigate the relevance of our interest rate factor by including it separately into a single-factor market model. Our second baseline regression is given in equation (2a), that is identical to early estimations of the interest rate sensitivity of common stocks, for instance used by Flannery & James (1984).

$$(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Level(5Y)_t + \epsilon_t \tag{2a}$$

Similarly to Bailey & Matyáš (2019), we also create a slope factor to determine if sensitivity to interest rates can be linked to changes in the slope of the yield curve. This equation is given in (2b).

$$(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Slope(10Y1Y)_t + \epsilon_t \tag{2b}$$

where $Slope(10Y1Y)_t$ is the slope factor.

The slope factor is given by the daily change in the spread between the yield on 10-year and 1-year maturity treasuries, implying that an increase in the magnitude of the factor is associated with a steepening of the yield curve.

Our regressions are made using OLS and we employ t-tests to measure significance of the exposure to the risk factors. We use Newey & West (1987) heteroscedasticity and autocorrelation robust (HAC) standard errors to compute our t-statistics. This is done to avoid any potential issue in inference caused by heteroscedasticity or autocorrelation in our sample.

3.3 Interest Rate Exposure and Bank Attributes

To understand what might drive the reversal in banks' interest rate sensitivity after the financial crisis, we divide our sample into different groups based on their change in reaction to interest rate fluctuations after the financial crisis. We apply the following regression specification to each individual bank in our sample:

$$(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(5Y)_t + \beta_{i,3} \cdot Level(5Y)_t \cdot FC + \epsilon_{i,t} \tag{3}$$

Where $(r_{i,t} - rf_t)$ are the individual bank returns and FC takes the value 1 after the financial crisis; that is, dates after September 15th, 2008[4].

We only use the banks who report all three beta coefficients and that existed both before the crisis and after 2010 in our analysis. Subsequently, we sort each bank based on their $\beta_{i,3}$ into three different groups. Ranked from the most negative to most positive beta, the first group is below the 10th percentile, the second group (50th) is between the 40th and 60th percentile, and the third group is above the 90th percentile. From each group, we then obtain summary statistics on our nine attributes. This is done by first calculating variable means over the post-crisis period[5] for each individual bank, to as a final step compute the statistics on an aggregate group level. This allows us to draw conclusions about what attributes are possessed by the "average" bank in each group. We test for differences between the groups using the Wilcoxon-Mann-Whitney U-test as data on characteristics show signs of non-normality and observations are few. Data on attributes can be found for the majority of the banks in our sample, except for the maturity gap. Exact number of banks as well as further descriptions of how the different attributes are obtained and calculated can be found in Appendix C.

As a final exercise, we create sorted portfolios based on the extent to which banks rely on deposits as a source of funding. We divide the sum of each banks' demand and savings deposits by total liabilities to obtain their deposit ratio. Banks are then sorted based on percentiles into three different portfolios based on this ratio; banks above the 90th percentile, 50th between the 40th-60th percentile, and banks below the 10th percentile. This is done to investigate the effect the use of deposit funding has on interest rate risk exposure. Portfolios are formed four times per year at the beginning of every quarter. Breakpoints are based on all banks with deposit data[6]. This method of sorting allows us to be able to display differences in factor loadings based on deposit reliance. We test for the significance of differences in means using the method proposed by Austin & Hux (2002)[7].

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[4] September 15th, 2008 corresponds to the date Lehman Brothers filed for bankruptcy.

[5] We define the post crisis period as 2010-19.

[6] In our sample; 1164 of the 2058 banks in the period 1986 and onwards.

[7] They suggest using the percentage overlap to compute a z-test as follows, $z_test = sqrt(2) * 1.645 * (1 - p)$ where p is the percentage overlap of the mean confidence interval. Here, the formula is written for a 90% confidence interval. A z-value exceeding 1.645 would then make the means significantly different with p<0.1.

3.4 Time Frame

We split our sample into various subperiods to recognize potential shifts in patterns due to important regulatory or economic events. In 1999, the Glass-Steagall Act was partially repealed and the year also corresponds to the beginning of the dot-com bubble. 2010 marks the first year of our post-crisis period, as the financial crisis had its end in mid-2009. In 2010, the Dodd Frank Act was also established. Different from previous papers, we also divide our post-crisis period in two subperiods. Between 2010 and 2015, the federal funds rate has been very low with an average of 0.12%. Between 2016 and 2019, it has on average been 1.4%. Both post-crisis periods have low interest rates in contrast to the pre-crisis period, however, splitting them before and after 2015 allows us to capture patterns related to very low interest rates. Furthermore, we let the bankruptcy of the Lehman Brothers on September 15th, 2008 signify the start of the financial crisis.

4 Empirical Analysis

This section reports the results from our empirical tests. In section 4.1, we present the results of our regressions concerning banks' average economic risk exposures. In section 4.2, we analyze how this exposure depends on differences in nine chosen bank attributes. In section 4.2.1, we further investigate if banks' deposit business may be a potential driver of the reversal in banks' interest rate sensitivity after the financial crisis. We conclude by presenting robustness checks on our findings in section 4.3.

4.1 Banks' Economic Risk Exposures

This section reports the results of our regressions that uncover banks' average exposure to credit and interest rate risk. We begin our analysis by regressing the excess return of a portfolio of bank stocks on the credit and interest rate risk factors. Table 4.1 reports the results from this first regression specification:

$$(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot Level(5Y)_t + \beta_2 \cdot CreditRisk_t + \epsilon_t \tag{1a}$$

where $(r_{p,t} - rf_t)$ is the daily excess return on the constructed bank portfolio. $Level(5Y)_t$ is the interest rate risk factor and $CreditRisk_t$ is the credit risk factor. We estimate regression (1a) by OLS. To protect inference from being skewed by any autocorrelation or heteroscedasticity present in our sample, we employ Newey West "HAC" standard errors for computing t-statistics.

Table 4.1
Excess Return of a Bank Portfolio on the Interest Rate and Credit Risk Factor

	Dependent Variable: Excess Return of Bank Portfolio						
	1990-2019	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
Level(5Y)	-1.11^{***}	1.10^{***}	0.52^{**}	-1.01^{***}	-1.94^{***}	-2.62^{***}	-3.64^{***}
	(0.13)	(0.13)	(0.25)	(0.19)	(0.25)	(0.25)	(0.23)
Credit Risk	0.43^{***}	1.03^{***}	1.53^{***}	0.73^{***}	0.54^{*}	-0.29	-0.22
	(0.14)	(0.27)	(0.41)	(0.22)	(0.28)	(0.33)	(0.26)
Constant	0.001^{***}	-0.0000	0.001^{**}	0.001^{**}	-0.0001	0.001^{***}	0.001^{***}
	(0.0001)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0003)
N	7,609	1,210	1,225	1,230	1,236	1,479	987
R^2	0.05	0.08	0.07	0.06	0.11	0.19	0.34

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot Level(5Y)_t + \beta_2 \cdot CreditRisk_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $Level(5Y)_t$ the daily return on a portfolio of Treasury bonds with 5 year maturity and $CreditRisk_t$ is the daily excess return on 5 year BBB bonds orthogonalized from $Level(5Y)_t$. The full sample period spans daily observations from 1990-2019 divided over 6 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: $^{*}p<0.1$; $^{**}p<0.05$;$^{***}p<0.01$.

Our interest rate risk factor is proxied by the return on a portfolio of risk-free 5-year US treasury bonds. Since increased prices on bonds imply lower yields, increasing returns on our portfolio represents decreasing interest rates. Hence, a positive loading on the interest rate factor denotes a negative co-movement with interest rates, and vice versa. Our credit risk factor is orthogonally constructed from the excess return on a portfolio of BBB bonds. A positive loading on the credit factor implies that when risky loans on banks' balance sheets yield positive returns, so does bank equity.

Employing the same risk factors as described in Begenau et al. (2015) and used in Bailey & Matyáš (2019), regression (1a) allows us to specify how much of the average bank excess return can be explained by the economic risk factors that banks theoretically are exposed to. It is intuitive that loans and fixed income items on banks' balance sheets subject them to credit risk in the form of default risk of the borrower or issuer, and that their maturity transformation business exposes them to interest rate risk. However, as evidenced by table 4.1, interest rate and credit risk are only able to explain a small part of bank equity returns with an R^2 averaging only 5-34%. This is even less than Bailey & Matyáš who report an R^2 averaging 9-50% when using monthly data. Clearly, the credit risk and interest rate risk factor alone are not very successful in explaining variation in bank equity returns. In contrast, they do a significantly better job in explaining variation in bank asset returns, where Begenau et al. (2015) find that they explain 50-90%.

With the use of daily data instead of monthly, we obtain more significant coefficients on the interest rate factor than those presented by Bailey & Matyáš (2019). With the exception for the 1995-99 period, our coefficients are significant with $p<0.01$. The interest rate factor changes sign from positive to negative during 2000-04, and in accordance with Bailey & Matyáš it becomes increasingly negative over time. However, we find a weaker relationship between the credit risk factor and banks' excess equity returns as compared to Bailey & Matyáš. While these authors report credit risk factor coefficients with $p<0.01$ across the whole sample and for almost all subperiods, these coefficients are insignificant in our regression after the financial crisis. The loadings on the credit risk factor are positive before the financial crisis, while they are negative afterwards.

Coefficients from our regression (1a) should however be interpreted with caution and more accurate conclusions of banks' exposure to the risk factors can be drawn when controlling for the market factor. We use our regression (1b) and the resulting table can be found in Table A.1 in Appendix A. Adding the market to the regression improves the model's goodness of fit significantly. This is in line with the findings of Schuermann & Stiroh (2005) who highlight the market factor as the most important factor in explaining bank returns. Furthermore, it also turns the loading on the credit risk factor insignificant in all subperiods except for the period 2016-19, where the factor has a significant negative loading. A possible explanation to this negative exposure could be that banks use credit risk derivatives and therefore experience negative returns when low grade bonds experience positive returns.

Since the credit risk coefficient loses significance for most periods when controlling for the market factor, this indicates that the market factor takes on much of the same risk initially captured by the credit risk factor. The market factor also captures some of the risk previously captured by the interest rate factor, although it remains significant in a majority of the subperiods. We therefore chose to omit the credit risk factor and continue our analysis by further investigating the relevance of the interest rate factor. Additionally, since credit risk is also influenced by the prevailing level of interest rates, we see this factor as a key variable in capturing banks' economic risk exposures.

Table 4.2 reports the results from regression (2a) of bank excess equity returns on the market factor and the same interest rate factor as before. This is the same regression initially estimated by Flannery & James (1984) to evaluate interest rate sensitivity of stock returns. The same HAC standard errors as previously are used compute t-statistics for significance testing.

$$(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Level(5Y)_t + \epsilon_t \tag{2a}$$

where $(r_{p,t} - rf_t)$ is the daily excess return on the constructed bank portfolio. $(Mkt - r_f)_t$ is the market factor and $Level(5Y)_t$ is the interest rate risk factor.

Table 4.2

Excess Return of a Bank Portfolio on the Market and Interest Rate Factor

	Dependent Variable: Excess Return of Bank Portfolio								
	1980-2019	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	0.92^{***}	0.61^{***}	0.57^{***}	0.98^{***}	0.98^{***}	0.80^{***}	1.07^{***}	1.16^{***}	0.90^{***}
	(0.03)	(0.02)	(0.06)	(0.03)	(0.04)	(0.03)	(0.06)	(0.03)	(0.04)
Level(5Y)	-0.09^{**}	0.17^{***}	0.23^{***}	0.02	0.43^{***}	0.20^{**}	0.10	-0.57^{***}	-2.08^{***}
	(0.04)	(0.03)	(0.05)	(0.07)	(0.09)	(0.08)	(0.18)	(0.09)	(0.18)
Constant	0.0000	0.0000	−0.0001	0.0000	−0.0002	0.001^{**}	-0.001^{*}	0.0000	0.0003
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
N	9,986	1,247	1,248	1,250	1,251	1,243	1,250	1,498	999
R^2	0.62	0.64	0.71	0.61	0.67	0.56	0.65	0.77	0.65

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Level(5Y)_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $(Mkt - r_f)_t$ the daily market excess return, $Level(5Y)_t$ the daily return on a portfolio of Treasury bonds with 5 year maturity. The full sample period spans daily observations from 1980-2019 divided over 8 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

We observe from Table 4.2 that the market beta has been around 1 across the entire sample and all subperiods. This market beta for the banking industry is consistent with earlier literature such as Begenau & Stafford (2019) as well as with the findings by Bailey & Matyáš (2019). The interest rate factor, however, behaves differently over time. After the financial crisis, the loadings on our interest rate factor changes sign, which again is consistent with the findings of Bailey & Matyáš as well as with other researchers such as Ampudia & Van den Heuvel (2018) and Chakbazof & Sviberg (2020). During the period 2005-09, the loading is close to zero and insignificant, which most likely marks the shift from positive to negative.

An interesting observation is that the loading is less negative in the low-interest environment between 2010-15 when the federal funds rate averaged 0.12%, in contrast to the following period when the federal funds rate averaged 1.4%. As argued by Ampudia & Van den Heuvel, banks' profitability is threatened when rates are low or near zero. The key fact to this is banks' reluctance to pay negative rates on their deposits, as they likely would lose customers who would then choose to hold cash instead. This zero-lower bound on deposits compresses net interest margins in a low interest rate environment as banks' interest income drops with rates but the interest costs adjust only partially. The fact that the period 2016-19 shows a more negative reaction to decreases in interest rate, when interest rates have begun to rise from their all time low, is therefore surprising. Based on the previous stated arguments, banks' net interest margins should be less pressured in the period 2016-19 and thus react less negatively to decreases in interest rates as compared to the period before. Why this is not the case can have a number of explanations. First, Wang (2020) finds that the short-run pass-through of policy rates to deposit and loan rates is lower at lower rates. This would explain the increased sensitivity of banks' equity returns to interest rate changes in the period when rates have begun to rise. Second, after many years of low interest rates and compressed deposit spreads, banks may be financially constrained with low retained earnings. This may impact their lending capacity, and thus income, even in the years after extremely low rates. Hence, further decreases in interest rates in this state would worsen banks' financial situation. Another important implication of this finding is that the United States might still be at or below its "reversal interest rate" as introduced by Brunnermeier & Koby (2018). That is, the interest rate might still be low enough to hurt banks' profitability and therefore the accommodative monetary policy reverses its intended effect and becomes contractionary for lending.

To further understand banks' sensitivity to interest rates, we also test replacing the interest factor with the "slope factor" as introduced by Bailey & Matyáš (2019). Thereby we test if the sensitivity is related to the term premium's impact on banks' net interest margins. Table A.2 in Appendix A reports the findings of bank excess equity returns on the market factor and the slope factor proxied by the change in yield spread between 10-year and 1-year maturity treasuries.

A positive coefficient on the slope factor means that the bank stocks generally experience positive excess returns when the yield curve steepens. This is intuitive, as banks' maturity transformation business benefits from a larger gap between the long-term rates they charge for loans and the short-term rates they pay for deposits. We confirm the finding by Bailey & Matyáš (2019) that the coefficient is also significantly higher after the financial crisis than in previous periods, implying an increased sensitivity to the slope of the yield curve. Again, we observe that the sensitivity is significantly higher after 2015, when interest rates have begun to rise from their all time low. Again, this might be an effect of the lower short-run pass-through of policy rates to deposit and loan rates at lower rates, as found by Wang (2020). It might also be due to banks being financially constrained after years of low interest rates and compressed deposit spreads that reduces their lending capacity and income. At this state, a steepening of the yield curve could clearly benefit banks net interest margins by allowing them to impose higher loan rates.

To conclude this section, we run a regression with all the factors mentioned thus far; that is the market factor, interest rate factor, slope factor and credit risk factor. This regression can be found in Table A.3 in Appendix A. When adding all the factors to the same regression the interest rate factor retains its significance and familiar pattern; switching signs post the financial crisis. However, the slope factor is, like the credit factor, only significant in the last period of our sample, 2016-2019. We conclude that the interest rate factor is proficient in explaining equity returns while the capability and consistency of the slope and credit factor is deficient in comparison.

4.2 Interest Rate Exposure and Bank Attributes

In this second section of our empirical analysis, we attempt to uncover drivers in the reversal of interest rate sensitivity among banks after the financial crisis. We begin with sorting banks into different groups based on their post crisis reaction to interest rate changes, to subsequently compare characteristics between the different groups. Second, we create sorted portfolios based on deposit ratios, which is presented in section 4.2.1.

We run the following regression on each of the individual banks in our sample:

$$(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(5Y)_t + \beta_{i,3} \cdot Level(5Y)_t \cdot FC + \epsilon_{i,t} \quad (3)$$

Regression (3) is similar to regression (2a) but with an added interaction term where FC takes the value 1 after the financial crisis; that is, dates after September 15th, 2008[8]. By looking at the attributes of banks with different interaction terms, we can discern which type of bank is driving the observed reversal in exposure of our portfolio. Since our proxy for the level of interest rates is realized returns, which has an inverse relationship with interest rates, a negative interaction term beta indicates that the bank equity is negatively (positively) affected by decreasing (increasing) interest rates post-crisis. We create three groups based on this interaction beta[9] as well as report an aggregate for all banks with an interaction coefficient. Ranging from the lowest to the highest interaction term beta, the first group contains banks below the 10th percentile, the second group contains banks in the mid percentiles (40-60th), and the last group contains banks above the 90th percentile. Table 4.3 presents the reported attributes for the banks in our sample.

[8] This date corresponds to the day Lehman Brothers filed for bankruptcy.

[9] We only use complete cases for these groups i.e. banks that existed pre and post the financial crisis.

Table 4.3
Description of Bank Attributes

Attribute	Description
DEP	deposit ratio
AT	log of total assets
BM	book to market value
LD	loans to deposit ratio
LAT	loans to total assets ratio
GAP	maturity gap
IGAP	income gap
NPM	net profit margin
DR	derivatives to total assets ratio

The attributes are chosen with the preconception that they all impact or might tell us something about interest rate exposure. Table 4.4 reports the average value of each attribute in the period 2010-19 for the different groups, thus excluding banks that failed in the aftermath of the financial crisis. All differences in attributes between the 10th and 90th percentile group are significant with at least $p<0.05$, except for the loans-to-assets ratio and maturity gap, which are insignificant. Details on p-values are available in Table A.6 in Appendix A. Further summary statistics for these attributes and how they are computed can be found in Appendix A Table A.4 and Appendix C respectively.

Table 4.4
Attributes of Banks with Different Post Crisis Interest Rate Exposure

	Statistic	Beta	DEP	AT	BM	LD	LAT	GAP	IGAP	NPM	DR
	Mean	−1.521	0.581	8.960	0.934	1.438	0.684	48.638	0.168	0.145	0.067
10th	Median	−1.442	0.594	8.340	0.838	1.324	0.675	47.209	0.155	0.157	0.024
	N	49	38	47	49	38	38	5	38	48	38
	Mean	−0.422	0.484	7.301	1.241	1.762	0.690	85.247	0.072	0.061	0.027
50th	Median	−0.411	0.495	7.086	1.110	1.622	0.705	84.020	0.081	0.102	0.008
	N	98	80	98	98	80	80	8	80	98	80
	Mean	0.520	0.448	7.089	1.241	2.363	0.675	37.475	0.049	0.027	0.042
90th	Median	0.450	0.430	7.031	1.154	1.692	0.669	33.921	0.048	0.055	0.002
	N	49	13	33	45	13	13	8	13	47	13
	Mean	−0.455	0.524	7.616	1.141	1.643	0.678	63.675	0.097	0.086	0.038
Full	Median	−0.411	0.526	7.291	1.018	1.473	0.688	59.955	0.099	0.118	0.012
	N	490	390	487	486	390	390	37	390	487	390

Note: Percentiles based on $\beta_{t,3}$ from the following model specification $(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(5Y)_t + \beta_{i,3} \cdot Level(5Y)_t \cdot FC + \epsilon_{i,t}$. $(r_{i,t} - rf_t)$ denotes daily bank excess returns, $(Mkt - r_f)_t$ is the daily market excess return, $Level(5Y)_t$ the daily return on a portfolio of Treasury bonds with 5 year maturity, FC takes the value 1 after September 15th 2008. 10th represents banks below the 10th percentile, 50th banks between the 40th and 60th percentile, and 90th banks above the 90th percentile in regards to $\beta_{t,3}$. Full is statistics for all the banks with an interaction term. Means and medians are calculated first by bank, then by group, in the period 2010-19.

Deposit Ratio. The deposit ratio (DEP) measures demand and savings deposits over total liabilities. Investigating differences in deposit ratios is vital to confirm or deny our hypothesis that heavily deposit reliant banks are more negatively affected by decreases in interest rates post-crisis. The underlying theory is that banks' reluctance to pay negative rates compresses bank net interest margins when rates decrease further from already low levels. This is because banks' interest income will decrease along with rates, but the zero lower bound causes interest costs to adjust only partially. Therefore, further decreases in interest rates will ultimately negatively affect those with a lot of deposits on their balance sheets. Our findings in table 4.4 are in consensus with this theory, as the banks in the 10th percentile have a higher deposit ratio compared to the other banks in our sample. Across the groups, deposit ratio increases the more negative the interaction term gets. Thus, our result indicates that deposit reliant banks react more negatively to decreases in interest rates post-crisis, and vice versa. This is in line with findings by Ampudia & Van den Heuvel (2018) and is further developed in section 4.2.1.

Total Assets. We use the logarithm of total assets (AT) as a measure of bank size. We observe that the banks who react most negatively to a decrease in interest rates after the financial crisis are the largest ones. English et al. (2018) have found that larger banks react more negatively to an increase in interest rates before the financial crisis. Thus, larger banks appear to have an increased exposure to interest rates, both before and after the financial crisis and irrespective of the direction of the reaction, which for instance has been confirmed by Chakbazof & Sviberg (2020). This could be explained by higher risk-taking among larger banks, for example by increasing interest rate exposure using derivatives. English et al. find that interest rate derivatives are more common among larger banks and we report a positive correlation between the two attributes in our sample too (see table A.5 in Appendix A). Furthermore, Begenau et al. (2015) find that derivatives historically have increased exposure to interest rate risk among banks. Another explanation for the relatively larger sensitivity for larger banks could be that returns of smaller banks in part are being driven by idiosyncratic factors like rumors of mergers and acquisitions, which would allow for less of the variation in returns to be explained by interest rate sensitivity.

Book-to-Market. A high book-to-market (BM) ratio implies that the stock is valued cheaply as compared to its book value. We would expect banks with a lower BM ratio to be more positively affected by decreasing interest rates compared to the average bank, as their relatively higher market valuation stems from higher projected future cash flows, whose value will increase from lower rates. Surprisingly, table 4.4 reports that stocks with a low BM ratio are more prevalent in the 10th percentile, that is, they are more negatively affected by decreasing interest rates post-crisis. However, it is natural that the described discounting effect is smaller in times of low rates due to compound interest. Nevertheless, our results point toward this effect being outweighed by others after the financial crisis but it may also be a matter of correlation between variables. Fama & French (1992) find patterns of the book-to-market ratio declining with the size of the bank, which is true for our sample as well (see table A.5 appendix A). If we consider this correlation, the observed pattern is less surprising given that bank size decreases along with the BM ratio, and larger banks are over-represented in the 10th percentile.

Loans-to-Deposit. The loans-to-deposit ratio (LD) is a measure of bank liquidity. A high LD ratio implies that the bank may not have enough liquidity to be able to cover unforeseen events. However, too low of a ratio might imply a poor return on assets. Table 4.4 reports that banks with a low LD ratio are more negatively affected by decreases in interest rates after the financial crisis than other banks. This could have two potential explanations. During low interest rates, deposit spreads are, according to our hypothesis, compressed. To compensate for this, banks need to increase their income from loans. Our results point towards that banks with a low LD ratio are unable to do so and thus react negatively to decreases in rates as this further compresses their net interest margins. Conversely, banks with a high LD ratio are negatively affected by rate increases post-crisis. At low rates, there is a heightened risk of depositors making withdrawals as the opportunity cost of cash is perceived lower. If interest rates then increase, there is a risk that more loan-takers will default on their loans. As a total effect, banks with a high LD may have a liquidity shortfall when rates increase in a low rate environment. Furthermore, a low LD ratio implies a high deposit ratio; their correlation is -0.89 in our sample. As previously mentioned, banks with the highest deposit ratio are among those who react most negatively to decreases in interest rates post crisis. Hence, the same effect is likely captured using this ratio.

Loans-to-Total-Assets. Similarly to the LD ratio, the loans-to-total assets ratio (LAT) is another measure of liquidity. A high ratio indicates that the bank has a lot of their balance sheet tied up in loans. Table 4.4 reports no clear pattern regarding this attribute and differences between groups are insignificant. Thus, a lot of loans in relation to the size of banks balance sheets does not seem to be a driver in the reversal of interest rate sensitivity among banks post-crisis.

Maturity Gap. The maturity gap (GAP) is the average amount of time in months that assets and liabilities differ in maturity. We utilize the methodology of measuring this mismatch introduced by English et al. (2018), explained at length in Appendix C. Despite using different maturity gap measures, researchers like Flannery & James (1984) and Akella & Greenbaum (1992) find that a larger maturity gap causes banks' share prices to decline more when interest rates increase. English et al. however, finds that before the financial crisis, a large maturity gap attenuates the negative effect of a surprise rise in interest rates. Figure 4.4 reports no clear pattern regarding this measure, as well as insignificant results, which may be due to our scarce maturity gap information for the banks in our sample; this information was only found for 37 of the 490 banks who reported an interaction term beta. Thus, any observations made should be interpreted with caution. We therefore also include the "income gap" to measure the impact of banks' maturity transformation business on their post crisis interest rate exposure.

Income Gap. To complement the shortage of data for our previous variable "maturity gap", we also look at banks' "income gap" (IGAP). As proposed by Flannery & James (1984) as a measure of maturity gap, and later used under the name income gap by Landier et al. (2013), it is the dollar difference between assets and liabilities which are repriced within a year's time, normalized by total assets. We find that banks with larger income gaps are more prevalent in the 10th percentile, i.e. among the banks with the most amplified interest rate exposure. Our findings are in line with those of Flannery & James and Akella & Greenbaum (1992), who argue that a larger income gap implies increased interest rate exposure. However, our results speak against the findings by Drechsler et al. (2018), who argue that maturity transformation does not expose banks to interest rate risk.

Net Profit Margin. The net profit margin (NPM) is the net income as a fraction of sales. Our results indicate that banks that have a more negative reaction to decreases in interest rates after the financial crisis have a higher average net profit margin. We find a positive correlation between bank size and net profit margin (see table A.5 in Appendix A), and it has been found that on average, larger banks have higher profitability (Regehr & Sengupta, 2016). Thus, since larger banks are more prevalent in the 10th percentile, this result is unsurprising. This measure, which is an average of all banks in each percentile over time, does not allow us to draw conclusions regarding the effects of interest rates on bank profitability. However, we can conclude that banks that are the main drivers in the reversal of interest rate sensitivity after the financial crisis, are on average banks with good profitability.

Derivatives Ratio. The derivatives ratio (DR) corresponds to interest rate derivatives held for non-trading purposes, over total assets. These derivatives can for instance be used to hedge interest rates. Table 4.4 shows evidence that the banks with the highest usage of these derivatives are most negatively affected by interest rate decreases after the financial crisis. Partly, this may be due to a correlation between bank size and derivatives usage. As reported by Office of the Comptroller of the Currency (2019), a small group of large financial institutions dominate derivatives activity in the United States banking system. English et al. (2018) finds that interest rate derivatives are more common among larger banks and we report a positive correlation between the two characteristics in our sample (see table A.5 in Appendix A). Since larger banks are more prevalent in the 10th percentile, it could thus explain the observed higher average derivatives ratio in this group. However, our results may also point in the direction that derivatives are used to increase interest rate exposure, rather than to hedge it. Accordingly, Begenau et al. (2015) find that derivatives not held for trading historically have increased exposure to interest rate risk, rather than hedged it.

In conclusion, our results from this section suggest that no single characteristic is alone the driver of the reversal, but possibly a combination of several. We find support for high deposit reliance being a driver behind the reversal of interest rate exposure. Additionally, we find evidence that banks with large balance sheets, low book-to-market ratios, low loans-to-deposit ratios, higher income gaps, higher net profit margins, and higher derivatives ratios are also contributors to the reversal.

4.2.1 Deposits as a Potential Driver of the Reversal

To further investigate whether banks' deposit business is a main driver in the shift of their interest rate exposure after the financial crisis, we generate sorted portfolios based on the extent to which banks rely on deposits for funding. As previously stated, banks should be negatively affected by decreases in interest rates in times of low rates. This is based on the notion presented by both Ampudia & Van den Heuvel (2018) and Wang (2020), arguing that banks are hesistant to pay negative rates on deposits which compresses their net interest margins. Thus, the deposit business of banks is a possible driver in the reversal of banks' interest rate sensitivity after the financial crisis.

We use the same measure of deposit funding as Chakbazof & Sviberg (2020) i.e. the ratio of demand and savings deposits to total liabilities. Banks are sorted based on percentiles into three different portfolios based on this ratio; banks above the 90th percentile, 50th between the 40th-60th percentile, and banks below the 10th percentile. Our first sorted portfolio begins on October 1st 1986, since this is when the first data on deposits is available. The deposit ratios signifying the average breaking points of the different portfolios pre and post crisis are presented in table A.7 in Appendix A. Furthermore, Figure A.1 (Appendix A) reports the distribution of deposit ratios across the entirety of our sample.

Table 4.5 reports regression (2a) for the three portfolios as well as the full sample of banks with deposit data, before and after the financial crisis. The "pre" period is from October 1st 1986 until September 15th, 2008. The "post" period is between 2010-2019.

Table 4.5

Deposit Sorted Portfolio Returns on Level(5Y) Pre and Post the Financial Crisis

	Dependent Variable: Excess Return of Bank Portfolio							
	Pre				**Post**			
DEP	All	90th	50th	10th	All	90th	50th	10th
(Mkt-r_f)	0.90***	0.72***	0.89***	0.98***	1.09***	1.04***	1.01***	1.04***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
Level(5Y)	0.04	−0.06	0.07	0.03	−1.08***	−1.23***	−1.00***	−0.94***
	(0.06)	(0.07)	(0.07)	(0.08)	(0.11)	(0.12)	(0.11)	(0.10)
Constant	0.0000	0.0002	0.0001	−0.0001	0.0001	0.0001	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
N	5,482	5,482	5,482	5,482	2,497	2,497	2,497	2,497
R^2	0.57	0.41	0.49	0.45	0.71	0.64	0.65	0.62

Note: This table presents the results from sorting the banks in our sample into portfolios based on deposit ratios. 90th denotes a portfolio of banks above the 90th percentile in regards to deposit ratio, 50th a portfolio of banks in the 40th-60th percentile, and 10th a portfolio of banks below the 10th percentile. For each portfolio, the following OLS regression is run before and after the financial crisis: $(r_{i,t} - rf_t) = \alpha + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(5Y)_t + \epsilon_{i,t}$, where $(r_{i,t} - rf_t)$ denotes the excess returns of the different portfolios, $(Mkt - r_f)_t$ the daily market excess return, $Level(5Y)_t$ the daily return on a portfolio of Treasury bonds with 5 year maturity. The pre-crisis period spans from October 1st 1986 until September 15th 2008. The post crisis period is 2010-19.T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Before the crisis, the loadings on the interest rate factor are small, insignificant and show no clear pattern. In the post-crisis period, we see patterns supporting the notion that banks with a large amount of deposits in relation to total liabilities (that is, banks in the 90th percentile) experience an increased negative exposure to interest rate risk. We find the difference between the $Level(5Y)$ coefficients for the 90th and 10th groups to be be significant with $p<0.1$ using the method proposed by Austin & Hux (2002). Figure A.2 in appendix A reports 90% confidence intervals for the the two coefficients. Our findings support the theory that when rates are low, banks with a lot of deposits react negatively to further decreases in interest rates as it compresses their net interest margins. Conversely, when rates increase, our findings imply that banks with a high deposit ratio benefit as it widens their net interest margins. This positive effect may be amplified due to "sticky" deposit rates as observed for instance by Hannan & Berger (1991) and Driscoll & Judson (2013). In times of increasing rates, the deposit rates of banks are slow to follow, adjusting to changes weeks or even months later and by less than the actual change in the federal funds rate. This increases the spread between deposit rates and loan rates and thus net interest margins. Banks that depend heavily on deposits as a source of funding can take greater advantage of this effect.

Furthermore, we find structural changes that may be contributors to the reversal in banks' interest rate sensitivity post-crisis. First, we find that the average deposit ratio has increased in the post-crisis period. This implies that banks' negative (positive) reaction to decreases (increases) in interest rates should be amplified in current times. Second, banks have become increasingly concentrated post crisis (Federal Deposit Insurance Corporation, n.d), which implies increased market power for the remaining banks. Banks with a lot of market power have more freedom to set the level of their deposit rates as their depositors perceive opportunity costs as lower. This can further explain banks being able to take advantage of the rising rates through their deposit business in the years following the financial crisis.

Continuing with the same three deposit sorted portfolios, we also test their exposure to the slope factor from regression (2b). The results are found in table A.8 in Appendix A. Consistent with our earlier results, we find that banks have an increased sensitivity to the slope of the yield curve post-crisis. This effect is again larger for banks with a lot of deposits on their balance sheets, although the pattern is not as clear as for the interest rate factor. An explanation to this can again be due to the low interest rate environment. When interest rates are low, banks with much deposits will benefit more from the yield curve steepening, as the rate on long-term loans increases while the deposit rates remain "sticky" at lower interest rates. This phenomena is beneficial for banks' net interest margins. In contrast, when the yield curve flattens, banks with much deposits will be negatively affected as loan rates decrease while the deposit rates are restricted by the zero lower bound. This again compresses the net interest margins of banks, hurting bank profitability.

4.3 Robustness of Empirical Results

To reassure robustness of our empirical findings, we perform several tests. The resulting tables are available in Appendix B for reference. First, we reconstruct our interest rate factor using the returns on both a portfolio of 10-year and 1-year treasury bonds. For regression (1a), this yields similar results for our interest rate factor as when using the 5-year portfolio. As previously concluded, the credit risk factor remains not robust; although it gains significance with both of the alternative maturities, the loadings differ significantly. For regressions (1b) and (2a) the alternative maturities yield similar results as when using the original factor. Using the 1-year bond generally increases the magnitude of interest rate factor loadings, while the 10 year bond decreases them. This is due to coefficients being scaled in the opposite direction of the slope of the yield curve. Since the yield curve has generally been upward sloping during our sample period, this implies smaller returns on the shorter-maturity portfolios, and larger on the longer-maturity portfolios. Hence, the loadings will be greater for shorter maturities, and vice versa.

For section 4.2, using the 10-year portfolio yields similar results, although the results for the loans-to-deposit ratio also becomes insignificant. With the 1-year portfolio, the majority of the results from Table 4.4 becomes insignificant and some of the patterns change. When using the alternative maturities on regression (2a) for our sorted portfolios in section 4.2.1, they yield similar findings as in our original regression.

Robustness of our findings in regression (2b) is tested by reconstructing our slope factor to the difference between the yield of a 5-year treasury bond and that of a 1-year treasury bond. This yields similar results as when using our original slope factor, which is the difference between the yield of a 10-year treasury bond and that of a 1-year treasury bond. When running this regression on our sorted portfolios in section 4.2.1, they too yield similar results as our original regression.

5 Conclusion

This paper examines the relationship between bank equity returns and their economic risk factors over time and how it varies with different bank attributes. With the use of daily data, we empirically confirm the findings by Bailey & Matyáš (2019) that the economic risk factors banks theoretically are exposed to, interest rate risk and credit risk, are solely unsuccessful in explaining variation in bank equity returns. The market factor does a significantly better job. Likewise, we confirm that prior to the financial crisis, bank stock returns were positively impacted by decreases in interest rates, but after the financial crisis this relationship has reversed. Surprisingly, we find that the banking industry is more sensitive to both the level and the slope of the yield curve after 2015, when rates have begun to rise from their all time low.

Furthermore, we find indications that large, profitable banks with heavy deposit reliance are driving the observed reversal in interest rate sensitivity, as these on average have the most negative change in their reaction to decreases in interest rates post crisis. This supports our initial hypothesis and the notion presented by Ampudia & Van den Heuvel (2018) that banks' reluctance to pay negative rates compresses bank net interest margins when rates decrease further from already low levels. This is because banks' interest income will decrease along with rates, but the zero lower bound causes interest costs to adjust only partially. Additionally, we find evidence that banks with lower book-to-market ratios, lower loans-to-deposit ratios, higher income gaps, and higher derivatives ratios are also contributors to the reversal.

Our findings imply that with rates near or below zero, the average bank's profitability will suffer from further rate decreases. Although rate cuts are meant to be expansionary, they may thus instead contract lending. For equity investors, our findings imply that investing in bank stocks is in the current environment primarily a bet on the market, but also seemingly a bet on interest rates.

To further understand banks' macroeconomic risk exposures during low interest rates, we suggest further studies investigating the relationship between rates and banks' accounting profitability in a low interest rate environment. Thereby, the hypothesis presented by Ampudia & Van den Heuvel (2018) could be further tested. Finally, we suggest deeper investigations into how each individual attributes used in our study interact with interest rates.

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Appendices

A Additional Tables and Figures

Table A.1
Excess Bank Portfolio Returns on Market, Interest Rate, and Credit Risk Factor

	Dependent Variable: Excess Return of Bank Portfolio						
	1990-2019	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	1.00***	0.98***	0.97***	0.80***	1.08***	1.15***	0.92***
	(0.02)	(0.03)	(0.04)	(0.03)	(0.06)	(0.03)	(0.04)
Level(5Y)	−0.11*	0.06	0.42***	0.19**	0.08	−0.57***	−2.06***
	(0.06)	(0.08)	(0.09)	(0.08)	(0.18)	(0.10)	(0.16)
Credit Risk	−0.23**	0.15	0.16	−0.08	−0.41	−0.15	−0.84***
	(0.10)	(0.12)	(0.22)	(0.13)	(0.29)	(0.14)	(0.17)
Constant	0.0000	0.0000	−0.0002	0.001*	−0.001*	0.0001	0.0004*
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
N	7,609	1,210	1,225	1,230	1,236	1,479	987
R^2	0.63	0.61	0.67	0.56	0.65	0.77	0.66

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - rf)_t + \beta_2 \cdot Level(5Y)_t + \beta_3 \cdot CreditRisk_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns,$(Mkt - rf)_t$ the daily market excess return, $Level(5Y)_t$ the daily return on a portfolio of Treasury bonds with 5 year maturity and $CreditRisk_t$ is the daily excess return on 5 year BBB bonds orthogonalized from $Level(5Y)_t$. The full sample period spans daily observations from 1990-2019 divided over 6 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table A.2
Excess Return of a Bank Portfolio on the Market and Slope Factor

	Dependent Variable: Excess Return of Bank Portfolio								
	1980-2019	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	0.92***	0.64***	0.58***	0.99***	0.98***	0.78***	1.06***	1.16***	0.97***
	(0.03)	(0.02)	(0.07)	(0.03)	(0.04)	(0.03)	(0.06)	(0.03)	(0.04)
Slope(10Y1Y)	0.83***	0.30**	−0.58**	0.45	−1.46**	−0.32	0.24	2.16***	10.06***
	(0.20)	(0.12)	(0.25)	(0.40)	(0.69)	(0.52)	(1.23)	(0.53)	(1.09)
Constant	0.0000	0.0001	0.0000	0.0000	−0.0001	0.001**	−0.001*	−0.0000	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
N	9,986	1,247	1,248	1,250	1,251	1,243	1,250	1,498	999
R^2	0.62	0.63	0.71	0.61	0.66	0.55	0.65	0.77	0.63

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Slope(10Y1Y)_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $(Mkt - r_f)_t$ the daily market excess return, $Slope(10Y1Y)_t$ the daily change in the spread between the yield on 10-year and 1-year maturity treasuries. The full sample period spans daily observations from 1980-2019 divided over 8 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table A.3

Excess Bank Portfolio Returns on Market, Interest Rate, Slope, and Credit Risk Factor

	Dependent Variable: Excess Return of Bank Portfolio						
	1990-2019	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	1.00***	0.99***	0.97***	0.80***	1.08***	1.16***	0.91***
	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)	(0.03)	(0.04)
Level(5Y)	−0.03	0.08	0.42***	0.19**	0.08	−0.73***	−1.76***
	(0.07)	(0.08)	(0.10)	(0.09)	(0.20)	(0.21)	(0.18)
Slope(10Y1Y)	1.10**	0.62	0.08	−0.03	−0.08	−1.04	2.87***
	(0.44)	(0.42)	(0.79)	(0.68)	(1.40)	(1.16)	(1.11)
Credit Risk	−0.13	0.19	0.17	−0.09	−0.42	−0.25	−0.60***
	(0.10)	(0.13)	(0.23)	(0.14)	(0.28)	(0.16)	(0.18)
Constant	−0.0000	0.0000	−0.0002	0.001*	−0.001*	0.0001	0.0004*
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
N	7,609	1,210	1,225	1,230	1,236	1,479	987
R^2	0.64	0.61	0.67	0.56	0.65	0.77	0.66

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - rf)_t + \beta_2 \cdot Level(5Y)_t + \beta_3 \cdot Slope(10Y1Y) + \beta_4 \cdot CreditRisk_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $(Mkt - r_f)_t$ the daily market excess return, $Level(5Y)_t$ the daily return on a portfolio of Treasury bonds with 5 year maturity, $Slope(10Y1Y)_t$ the daily change in the spread between the yield on 10-year and 1-year maturity treasuries, and $CreditRisk_t$ is the excess return on 5 year BBB bonds orthogonalized from $Level(5Y)_t$. The full sample period spans daily observations from 1990-2019 divided over 6 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows *p<0.1; **p<0.05;***p<0.01.

Table A.4

Summary Statistics of Attributes

Statistic	Interaction	DEP	AT	BM	LD	LAT	GAP	IGAP	NPM	DR
Min	−2.653	0.084	4.780	0.284	0.510	0.326	10.870	−0.353	−0.471	0.000
Pctl(25)	−0.815	0.430	6.621	0.814	1.193	0.630	41.902	0.012	0.040	0.000
Mean	−0.455	0.524	7.616	1.141	1.643	0.678	63.675	0.097	0.086	0.038
Median	−0.411	0.526	7.291	1.018	1.473	0.688	59.955	0.099	0.118	0.012
Pctl(75)	−0.086	0.628	8.401	1.347	1.863	0.743	88.215	0.184	0.172	0.042
Max	1.453	0.832	14.700	3.386	10.304	0.861	135.150	0.496	0.320	0.433
St. Dev.	0.583	0.141	1.491	0.494	0.860	0.096	29.669	0.155	0.132	0.065
N	490	390	487	486	390	390	37	390	487	390

Note: This table reports summary statistics of all banks that have an interaction term. Values are reported on an aggregate bank level. DEP is the ratio of deposit to total liabilities, AT is the log of total assets, BM is the book to market ratio, LD the loans to derivatives ratio, LAT the loans to total assets ratio, GAP the maturity gap, IGAP the income gap, NPM the net profit margin, and DR the derivatives to total assets.

Table A.5

Attributes Correlation Matrix

	DEP	AT	BM	LD	LAT	GAP	IGAP	NPM	DR
DEP	1								
AT	0.394	1							
BM	-0.304	-0.400	1						
LD	-0.893	-0.387	0.285	1					
LAT	0.183	0.075	-0.076	0.082	1				
GAP	-0.190	−0.119	0.087	0.185	−0.300	1			
IGAP	0.279	0.092	−0.239	−0.159	0.304	−0.655	1		
NPM	0.264	0.257	−0.563	−0.234	0.104	0.216	0.030	1	
DR	0.315	0.329	−0.100	−0.213	0.269	−0.138	0.303	0.079	1

Note: This table reports a correlation matrix of all attributes in Table 4.4. DEP is the ratio of deposit to total liabilities, AT is the log of total assets, BM is the book to market ratio, LD the loans to derivatives ratio, LAT the loans to total assets ratio, GAP the maturity gap, IGAP the income gap, NPM the net profit margin, and DR the derivatives to total assets.

Table A.6

Significance of Bank Attributes Level(5Y)

Attribute	Hypothesis	P-Value
DEP	10th>90th	0.0043***
AT	10th>90th	0.0000***
BM	10th<90th	0.0002***
LD	10th<90th	0.0170**
LAT	10th>90th	0.370
GAP	10th>90th	0.2176
IGAP	10th>90th	0.0170**
NPM	10th>90th	0.0000***
DR	10th>90th	0.0261**

Note: This table reports the p-values from Wilcoxon-Mann-Whitney U-tests between the groups below the 10th percentile and above the 90th pecentile in regards to $\beta_{i,3}$ from the following regression $(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(5Y)_t + \beta_{i,3} \cdot Level(5Y)_t \cdot FC + \epsilon_{i,t}$. DEP is the ratio of deposit to total liabilities, AT is the log of total assets, BM is the book to market ratio, LD the loans to derivatives ratio, LAT the loans to total assets ratio, GAP the maturity gap, IGAP the income gap, NPM the net profit margin, and DR the derivatives to total assets.

Table A.7

Deposits Ratio Percentile Breakpoints

DEP Percentile	Pre	Post
90th	0.575	0.737
50th	0.391	0.549
10th	0.249	0.356

Note: This table reports the average ratio of Savings and Demand deposits to Total Liabilities before and after the financial crisis of different percentile groups. The pre-crisis period spans from October 1st 1986 until September 15th 2008. The post crisis period is 2010-19.

Table A.8

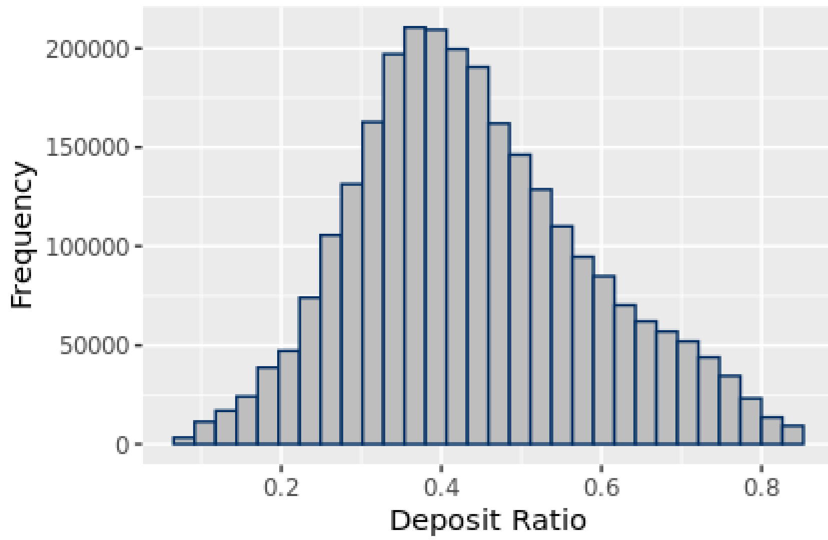
Deposit Sorted Portfolio Returns on the Slope(10Y1Y) Pre and Post the Financial Crisis

	Dependent Variable: Excess Return of Bank Portfolio							
	Pre				**Post**			
DEP	All	90th	50th	10th	All	90th	50th	10th
(Mkt-r_f)	0.89***	0.72***	0.88***	0.98***	1.11***	1.06***	1.02***	1.04***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
Slope(10Y1Y)	−0.13	0.08	−0.37	0.14	4.35***	5.02***	3.97***	4.14***
	(0.37)	(0.33)	(0.41)	(0.47)	(0.59)	(0.58)	(0.56)	(0.65)
Constant	0.0000	0.0002	0.0001	−0.0001	0.0000	0.0000	−0.0000	−0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
N	5,482	5,482	5,482	5,482	2,510	2,510	2,510	2,510
R^2	0.57	0.41	0.49	0.45	0.70	0.63	0.64	0.62

Note: This table presents the results from sorting the banks in our sample into portfolios based on deposit ratios. 90th denotes a portfolio of banks above the 90th percentile in regards to deposit ratio, 50th a portfolio of banks in the 40th-60th percentile, and 10th a portfolio of banks below the 10th percentile. For each portfolio, the following OLS regression is run before and after the financial crisis: $(r_{i,t} - rf_t) = \alpha + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Slope(10Y1Y)_t + \epsilon_{i,t}$, where $(r_{i,t} - rf_t)$ denotes the excess returns of the different portfolios, $(Mkt - r_f)_t$ the daily market excess return, $Slope(10Y1Y)_t$ the daily change in the spread between the yield on 10-year and 1-year maturity treasuries. The pre-crisis period spans from October 1st 1986 until September 15th 2008. The post crisis period is 2010-19. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Figure A.1

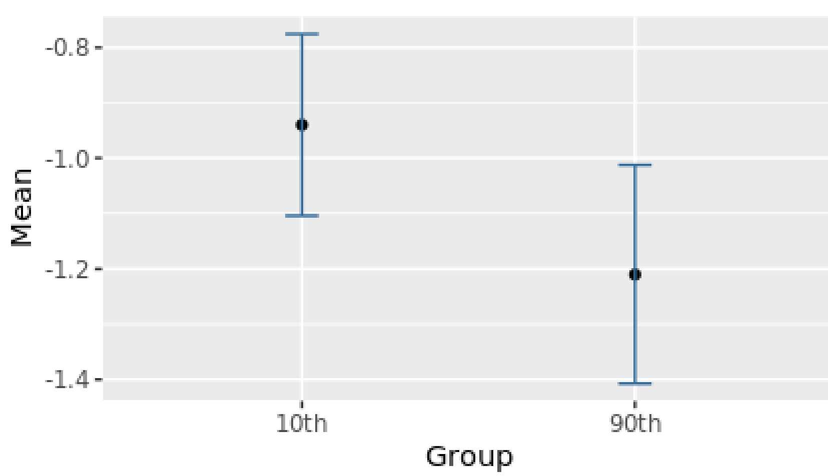
Deposit Ratio Distribution



Note: This figure shows the distribution of the deposit ratio - total savings and demand deposits to total liabilities in our sample in which 1164 banks have data on deposits. The full sample period spans from 1980-2019

Figure A.2

Mean Confidence Interval of Post Crisis Interest Rate Exposure



Note: This figure shows 90% confidence intervals of beta coefficient 2 from the following regression $(r_{i,t} - rf_t) = \alpha + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(5Y)_t + \epsilon_{i,t}$ for the portfolios of banks with deposit ratios in the 10th percentile and above 90th.

B Robustness of Empirical Results

Table B.1

Excess Return of a Bank Portfolio on the Level(1Y) and Credit Risk Factor

	Dependent Variable: Excess Return of Bank Portfolio						
	1990-2019	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
Level(1Y)	-2.89^{***}	2.89^{***}	0.65	-2.91^{***}	-9.76^{***}	-4.24^{**}	-15.47^{***}
	(0.62)	(0.58)	(1.35)	(0.76)	(1.29)	(1.98)	(1.75)
Credit Risk	-0.52^{***}	1.23^{***}	1.15^{***}	-0.30^{**}	-0.43^{*}	-1.85^{***}	-2.11^{***}
	(0.11)	(0.19)	(0.23)	(0.15)	(0.23)	(0.20)	(0.21)
Constant	0.001^{***}	-0.0002	0.001^{**}	0.001^{***}	0.001	0.001^{***}	0.002^{***}
	(0.0002)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
N	7,609	1,210	1,225	1,230	1,236	1,479	987
R^2	0.02	0.08	0.07	0.03	0.10	0.14	0.25

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot Level(1Y)_t + \beta_2 \cdot CreditRisk_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $Level(1Y)_t$ the daily return on a portfolio of Treasury bonds with 1 year maturity and $CreditRisk_t$ is the daily excess return on 5 year BBB bonds orthogonalized from $Level(1Y)_t$. The full sample period spans daily observations from 1990-2019 divided over 6 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.2

Excess Return of a Bank Portfolio on the Level(10Y) and Credit Risk Factor

	Dependent Variable: Excess Return of Bank Portfolio						
	1990-2019	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
Level(10Y)	-0.70^{***}	0.80^{***}	0.46^{***}	-0.60^{***}	-1.14^{***}	-1.62^{***}	-2.14^{***}
	(0.08)	(0.08)	(0.16)	(0.11)	(0.18)	(0.14)	(0.13)
Credit Risk	0.76^{***}	0.49^{**}	1.20^{**}	0.92^{***}	0.41	1.28^{***}	0.52^{*}
	(0.16)	(0.23)	(0.53)	(0.24)	(0.37)	(0.31)	(0.29)
Constant	0.0005^{***}	-0.0000	0.001^{*}	0.001^{**}	-0.0003	0.001^{***}	0.001^{**}
	(0.0001)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0002)	(0.0003)
N	7,609	1,210	1,225	1,230	1,236	1,479	987
R^2	0.06	0.10	0.06	0.06	0.09	0.27	0.36

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot Level(10Y)_t + \beta_2 \cdot CreditRisk_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $Level(10Y)_t$ the daily return on a portfolio of Treasury bonds with 10 year maturity and $CreditRisk_t$ is the daily excess return on 5 year BBB bonds orthogonalized from $Level(10Y)_t$. The full sample period spans daily observations from 1990-2019 divided over 6 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.3
Excess Bank Portfolio Returns on Market, Level(1Y), and Credit Risk Factor

	Dependent Variable: Excess Return of Bank Portfolio						
	1990-2019	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	1.00***	0.98***	0.97***	0.79***	1.07***	1.17***	0.97***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.07)	(0.03)	(0.04)
Level(1Y)	0.36	0.26	1.29**	0.51*	0.57	−2.21**	−7.29***
	(0.30)	(0.37)	(0.56)	(0.28)	(1.14)	(1.09)	(1.09)
Credit Risk	−0.24***	0.08	0.31**	0.07	−0.20	−0.40***	−1.53***
	(0.06)	(0.09)	(0.14)	(0.09)	(0.21)	(0.09)	(0.14)
Constant	−0.0001	−0.0000	−0.0003	0.001*	−0.001*	0.0001	0.001***
	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
N	7,609	1,210	1,225	1,230	1,236	1,479	987
R^2	0.64	0.61	0.67	0.56	0.65	0.77	0.65

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - rf)_t + \beta_2 \cdot Level(1Y)_t + \beta_3 \cdot CreditRisk_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns,$(Mkt - rf)_t$ the daily market excess return, $Level(1Y)_t$ the daily return on a portfolio of Treasury bonds with 1 year maturity and $CreditRisk_t$ is the daily excess return on 5 year BBB bonds orthogonalized from $Level(1Y)_t$. The full sample period spans daily observations from 1990-2019 divided over 6 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.4
Excess Bank Portfolio Returns on Market, Level(10Y), and Credit Risk Factor

	Dependent Variable: Excess Return of Bank Portfolio						
	1990-2019	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	1.00***	0.98***	0.96***	0.79***	1.08***	1.15***	0.90***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.06)	(0.03)	(0.04)
Level(10Y)	−0.10***	0.02	0.20***	0.09*	0.08	−0.29***	−1.28***
	(0.04)	(0.05)	(0.06)	(0.05)	(0.11)	(0.06)	(0.10)
Credit Risk	−0.11	0.23*	0.38	−0.04	−0.54**	−0.21	−0.48**
	(0.10)	(0.13)	(0.23)	(0.14)	(0.27)	(0.15)	(0.19)
Constant	0.0000	0.0000	−0.0001	0.001**	−0.001*	0.0000	0.0003
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
N	7,609	1,210	1,225	1,230	1,236	1,479	987
R^2	0.63	0.61	0.67	0.56	0.65	0.77	0.67

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - rf)_t + \beta_2 \cdot Level(10Y)_t + \beta_3 \cdot CreditRisk_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns,$(Mkt - rf)_t$ the daily market excess return, $Level(10Y)_t$ the daily return on a portfolio of Treasury bonds with 10 year maturity and $CreditRisk_t$ is the daily excess return on 5 year BBB bonds orthogonalized from $Level(10Y)_t$. The full sample period spans daily observations from 1990-2019 divided over 6 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.5

Excess Bank Portfolio Returns on Market Factor and Level(1Y)

	Dependent Variable: Excess Return of Bank Portfolio								
	1980-2019	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	0.92^{***}	0.62^{***}	0.58^{***}	0.98^{***}	0.98^{***}	0.62^{***}	1.07^{***}	1.21^{***}	1.03^{***}
	(0.03)	(0.02)	(0.06)	(0.03)	(0.03)	(0.03)	(0.07)	(0.03)	(0.05)
Level(1Y)	0.31^{**}	0.79^{***}	1.00^{***}	0.17	1.86^{***}	0.79^{*}	0.51	-2.15^{*}	-9.37^{***}
	(0.14)	(0.10)	(0.17)	(0.34)	(0.51)	(0.30)	(1.08)	(1.11)	(1.30)
Constant	-0.0000	-0.0003	-0.0003^{*}	0.0000	-0.001^{**}	-0.0003^{*}	-0.001^{*}	-0.0000	0.001^{**}
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
N	9,986	1,247	1,248	1,250	1,251	1,247	1,250	1,498	999
R^2	0.62	0.65	0.71	0.61	0.67	0.65	0.65	0.76	0.59

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Level(1Y)_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $(Mkt - r_f)_t$ the daily market excess return, $Level(1Y)_t$ the daily return on a portfolio of Treasury bonds with 1 year maturity. The full sample period spans daily observations from 1980-2019 divided over 8 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.6

Excess Bank Portfolio Returns on Market Factor and Level(10Y)

	Dependent Variable: Excess Return of Bank Portfolio								
	1980-2019	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	0.92^{***}	0.61^{***}	0.56^{***}	0.98^{***}	0.97^{***}	0.61^{***}	1.07^{***}	1.14^{***}	0.89^{***}
	(0.03)	(0.02)	(0.06)	(0.03)	(0.04)	(0.04)	(0.07)	(0.03)	(0.04)
Level(10Y)	-0.08^{***}	0.13^{***}	0.16^{***}	-0.002	0.23^{***}	0.13^{*}	0.07	-0.30^{***}	-1.27^{***}
	(0.03)	(0.02)	(0.04)	(0.05)	(0.07)	(0.05)	(0.11)	(0.06)	(0.10)
Constant	0.0000	0.0000	-0.0000	0.0000	-0.0002	0.0000^{**}	-0.001^{*}	0.0000	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
N	9,986	1,247	1,248	1,250	1,251	1,247	1,250	1,498	999
R^2	0.62	0.64	0.72	0.61	0.67	0.64	0.65	0.77	0.67

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Level(10Y)_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $(Mkt - r_f)_t$ the daily market excess return, $Level(10Y)_t$ the daily return on a portfolio of Treasury bonds with 10 year maturity. The full sample period spans daily observations from 1980-2019 divided over 8 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.7

Excess Bank Portfolio Returns on Market Factor and Slope(5Y1Y)

	Dependent Variable: Excess Return of Bank Portfolio								
	1980-2019	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09	2010-15	2016-19
(Mkt-r_f)	0.92***	0.64***	0.58***	0.99***	0.97***	0.78***	1.05***	1.16***	0.97***
	(0.03)	(0.02)	(0.07)	(0.03)	(0.04)	(0.03)	(0.07)	(0.03)	(0.04)
Slope(5Y1Y)	0.88***	0.25*	−0.76**	0.57	−2.41***	−0.57	0.44	2.64***	10.77***
	(0.22)	(0.13)	(0.30)	(0.42)	(0.70)	(0.56)	(1.18)	(0.49)	(1.12)
Constant	0.0000	0.0001	0.0000	0.0000	−0.0001	0.001**	−0.001*	−0.0000	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
N	9,986	1,247	1,248	1,250	1,251	1,243	1,250	1,498	999
R^2	0.62	0.62	0.71	0.61	0.67	0.55	0.65	0.77	0.63

Note: This table presents the results from the following OLS regression $(r_{p,t} - rf_t) = \alpha + \beta_1 \cdot (Mkt - r_f)_t + \beta_2 \cdot Slope(5Y1Y)_t + \epsilon_t$. $(r_{p,t} - rf_t)$ denotes daily bank portfolio excess returns, $(Mkt - r_f)_t$ the daily market excess return, $Slope(5Y1Y)_t$ the daily change in the spread between the yield on 5-year and 1-year maturity treasuries. The full sample period spans daily observations from 1980-2019 divided over 8 subperiods. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.8

Attributes of Banks with Different Post Crisis Level(1) Exposure

	Statistic	Beta	DEP	AT	BM	LDR	LAT	GAP	IGAP	NPM	DR
	Mean	−6.682	0.541	8.115	1.289	1.536	0.679	66.069	0.146	0.067	0.050
10th	Median	−6.224	0.550	7.772	1.217	1.354	0.673	66.069	0.146	0.103	0.015
	N	49	30	44	47	30	30	1	30	46	30
	Mean	−1.211	0.549	7.653	1.058	1.514	0.667	75.398	0.115	0.112	0.031
50th	Median	−1.193	0.569	7.386	0.950	1.290	0.674	78.699	0.113	0.126	0.010
	N	98	81	97	97	81	81	4	81	97	81
	Mean	5.600	0.492	7.412	1.178	1.939	0.672	48.228	0.129	0.028	0.045
90th	Median	4.192	0.460	7.513	0.996	1.723	0.677	47.436	0.120	0.067	0.004
	N	49	24	41	47	24	24	10	24	47	23
	Mean	−1.053	0.524	7.616	1.141	1.643	0.678	63.675	0.097	0.086	0.038
Full	Median	−1.193	0.526	7.291	1.018	1.473	0.688	59.955	0.099	0.118	0.012
	N	490	390	487	486	390	390	37	390	487	390

Note: Percentiles based on $\beta_{t,3}$ from the following model specification $(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(1Y)_t + \beta_{i,3} \cdot Level(1Y)_t \cdot FC + \epsilon_{i,t}$. $(r_{i,t} - rf_t)$ denotes daily bank excess returns, $(Mkt - r_f)_t$ is the daily market excess return, $Level(1Y)_t$ the daily return on a portfolio of Treasury bonds with 1 year maturity, FC takes the value 1 after September 15th 2008. 10th represents banks below the 10th percentile, 50th banks between the 40th and 60th percentile, and 90th banks above the 90th percentile in regards to $\beta_{t,3}$. Full is statistics for all the banks with an interaction term. Means and medians are calculated first by bank, then by group, in the period 2010-19.

Table B.9

Attributes of Banks with Different Post Crisis Level(10) Exposure

	Statistic	Beta	DEP	AT	BM	LDR	LAT	GAP	IGAP	NPM	DR
	Mean	−0.935	0.575	8.947	0.978	1.497	0.688	54.879	0.166	0.133	0.070
10th	Median	−0.901	0.594	8.328	0.842	1.324	0.681	56.639	0.155	0.156	0.022
	N	49	38	46	49	38	38	4	38	47	38
	Mean	−0.257	0.504	7.298	1.209	1.742	0.689	84.285	0.067	0.084	0.032
50th	Median	−0.250	0.516	7.059	1.100	1.601	0.702	88.215	0.084	0.114	0.011
	N	98	78	98	98	78	78	9	78	98	78
	Mean	0.339	0.491	7.121	1.248	1.660	0.661	40.182	0.041	0.034	0.032
90th	Median	0.316	0.484	6.960	1.171	1.464	0.668	35.039	0.055	0.069	0.010
	N	49	12	32	44	12	12	7	12	46	12
	Mean	−0.277	0.524	7.616	1.141	1.643	0.678	63.675	0.097	0.086	0.038
Full	Median	−0.250	0.526	7.291	1.018	1.473	0.688	59.955	0.099	0.118	0.012
	N	490	390	487	486	390	390	37	390	487	390

Note: Percentiles based on $\beta_{t,3}$ from the following model specification $(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(10Y)_t + \beta_{i,3} \cdot Level(10Y)_t \cdot FC + \epsilon_{i,t}$. $(r_{i,t} - rf_t)$ denotes daily bank excess returns, $(Mkt - r_f)_t$ is the daily market excess return, $Level(10Y)_t$ the daily return on a portfolio of Treasury bonds with 10 year maturity, FC takes the value 1 after September 15th 2008. 10th represents banks below the 10th percentile, 50th banks between the 40th and 60th percentile, and 90th banks above the 90th percentile in regards to $\beta_{t,3}$. Full is statistics for all the banks with an interaction term. Means and medians are calculated first by bank, then by group, in the period 2010-19.

Table B.10

Significance of Bank Attributes Level(1Y)

Attribute	Hypothesis	P-Value
DEP	10th>90th	0.0982*
AT	10th>90th	0.0731*
BM	10th>90th	0.0580*
LD	10th<90th	0.1396
LAT	10th>90th	0.4759
GAP	10th>90th	0.2727
IGAP	10th>90th	0.3552
NPM	10th>90th	0.0785*
DR	10th>90th	0.2681

Note: This table reports the p-values from Wilcoxon-Mann-Whitney U-tests between the groups below the 10th percentile and above the 90th pecentile in regards to $\beta_{i,3}$ from the following regression $(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(1Y)_t + \beta_{i,3} \cdot Level(1Y)_t \cdot FC + \epsilon_{i,t}$. DEP is the ratio of deposit to total liabilities, AT is the log of total assets, BM is the book to market ratio, LD the loans to derivatives ratio, LAT the loans to total assets ratio, GAP the maturity gap, IGAP the income gap, NPM the net profit margin, and DR the derivatives to total assets.

Table B.11

Significance of Bank Attributes Level(10Y)

Attribute	Hypothesis	P-Value
DEP	10th>90th	0.0372**
AT	10th>90th	0.0000***
BM	10th<90th	0.0003***
LD	10th<90th	0.1211*
LAT	10th>90th	0.2503
GAP	10th>90th	0.2061
IGAP	10th>90th	0.0640*
NPM	10th>90th	0.0000***
DR	10th>90th	0.0609*

Note: This table reports the p-values from Wilcoxon-Mann-Whitney U-tests between the groups below the 10th percentile and above the 90th pecentile in regards to $\beta_{i,3}$ from the following regression $(r_{i,t} - rf_t) = \alpha_i + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(1Y)_t + \beta_{i,3} \cdot Level(1Y)_t \cdot FC + \epsilon_{i,t}$. DEP is the ratio of deposit to total liabilities, AT is the log of total assets, BM is the book to market ratio, LD the loans to derivatives ratio, LAT the loans to total assets ratio, GAP the maturity gap, IGAP the income gap, NPM the net profit margin, and DR the derivatives to total assets.

Table B.12

Deposit Sorted Portfolio Returns on the Level(1Y) Pre & Post the Financial Crisis

	Dependent Variable: Excess Return of Bank Portfolio							
	Pre				**Post**			
DEP	All	90th	50th	10th	All	90th	50th	10th
(Mkt-r_f)	0.90***	0.71***	0.89***	0.98***	1.18***	1.14***	1.09***	1.11***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
Level(1Y)	0.21	−0.34	0.22	0.18	−4.87***	−5.09***	−5.07***	−4.11***
	(0.26)	(0.26)	(0.27)	(0.35)	(0.92)	(1.11)	(1.01)	(0.97)
Constant	−0.0000	0.0003*	0.0000	−0.0002	0.0001	0.0001	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
N	5,482	5,482	5,482	5,482	2,497	2,497	2,497	2,497
R^2	0.57	0.41	0.49	0.45	0.69	0.62	0.63	0.61

Note: This table presents the results from sorting the banks in our sample into portfolios based on deposit ratios. 90th denotes a portfolio of banks above the 90th percentile in regards to deposit ratio, 50th a portfolio of banks in the 40th-60th percentile, and 10th a portfolio of banks below the 10th percentile. For each portfolio, the following OLS regression is run before and after the financial crisis: $(r_{i,t} - rf_t) = \alpha + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(1Y)_t + \epsilon_{i,t}$, where $(r_{i,t} - rf_t)$ denotes the excess returns of the different portfolios, $(Mkt - r_f)_t$ the daily market excess return, $Level(1Y)_t$ the daily return on a portfolio of Treasury bonds with 1 year maturity. The pre-crisis period spans from October 1st 1986 until September 15th 2008. The post crisis period is 2010-19. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.13

Deposit Sorted Portfolio Returns on the Level(10Y) Pre & Post the Financial Crisis

	Dependent Variable: Excess Return of Bank Portfolio							
	Pre				**Post**			
DEP	All	90th	50th	10th	All	90th	50th	10th
(Mkt-r_f)	0.90***	0.72***	0.89***	0.98***	1.07***	1.02***	0.99***	1.01***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
Level(10Y)	0.03	−0.03	0.04	0.04	−0.61***	−0.71***	−0.55***	−0.55***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.07)	(0.07)	(0.07)
Constant	0.0000	0.0002	0.0001	−0.0001	0.0001	0.0001	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
N	5,482	5,482	5,482	5,482	2,497	2,497	2,497	2,497
R^2	0.57	0.41	0.49	0.45	0.71	0.64	0.64	0.62

Note: This table presents the results from sorting the banks in our sample into portfolios based on deposit ratios. 90th denotes a portfolio of banks above the 90th percentile in regards to deposit ratio, 50th a portfolio of banks in the 40th-60th percentile, and 10th a portfolio of banks below the 10th percentile. For each portfolio, the following OLS regression is run before and after the financial crisis: $(r_{i,t} - rf_t) = \alpha + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Level(10Y)_t + \epsilon_{i,t}$, where $(r_{i,t} - rf_t)$ denotes the excess returns of the different portfolios, $(Mkt - r_f)_t$ the daily market excess return, $Level(10Y)_t$ the daily return on a portfolio of Treasury bonds with 10 year maturity. The pre-crisis period spans from October 1st 1986 until September 15th 2008. The post crisis period is 2010-19. T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

Table B.14

Deposit Sorted Portfolio Returns on the Slope(5Y1Y) Pre & Post the Financial Crisis

	Dependent Variable: Excess Return of Bank Portfolio							
	Pre				**Post**			
DEP	All	90th	50th	10th	All	90th	50th	10th
(Mkt-r_f)	0.89***	0.72***	0.89***	0.98***	1.12***	1.07***	1.03***	1.06***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
Slope(5Y1Y)	−0.05	0.24	−0.33	0.25	4.83***	5.62***	4.51***	4.46***
	(0.45)	(0.39)	(0.49)	(0.56)	(0.56)	(0.61)	(0.54)	(0.60)
Constant	0.0000	0.0002	0.0001	−0.0001	0.0000	0.0000	−0.0000	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
N	5,482	5,482	5,482	5,482	2,510	2,510	2,510	2,510
R^2	0.57	0.41	0.49	0.45	0.70	0.63	0.64	0.62

Note: This table presents the results from sorting the banks in our sample into portfolios based on deposit ratios. 90th denotes a portfolio of banks above the 90th percentile in regards to deposit ratio, 50th a portfolio of banks in the 40th-60th percentile, and 10th a portfolio of banks below the 10th percentile. For each portfolio, the following OLS regression is run before and after the financial crisis: $(r_{i,t} - rf_t) = \alpha + \beta_{i,1} \cdot (Mkt - r_f)_t + \beta_{i,2} \cdot Slope(5Y1Y)_t + \epsilon_{i,t}$, where $(r_{i,t} - rf_t)$ denotes the excess returns of the different portfolios, $(Mkt - r_f)_t$ the daily market excess return, $Slope(5Y1Y)_t$ the daily change in the spread between the yield on 5-year and 1-year maturity treasuries. The pre-crisis period spans from October 1st 1986 until September 15th 2008. The post crisis period is 2010-19.T-statistics are computed using Newey West HAC standard errors, errors are reported in parentheses. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

C Attributes Data and Calculations

Bank characteristics data is either retrieved from the Compustat Fundamental Annual database, the Bank Regulatory Database or the Financial Ratios Suite also supplied by WRDS. Below we provide a detailed description of how each characteristic is retrieved and calculated.

Deposit Ratio (DEP)
From the BHC section of the Bank Regulatory Database we retrieve the following balance sheet items; Total non-transaction savings deposits, Total demand deposits and Total liabilities and minority interest. The deposit ratio is then calculated as follows:

DEP = [Total non-transaction savings deposits (BHCB389) + Total demand deposits (BHCB2210)]/Total liabilities and minority interest(BHCK2948)

Data is supplied for 1164 of the banks in our sample.

Total Assets (AT)
Total assets are retrieved from the Compustat Fundamentals Quarterly database and then normalized using the natural logarithm.

AT = log(Total Assets)

Data is supplied for 1970 of the banks in our sample.

Book-to-Market (BM)
The book-to-market values are taken from the Financial Ratios Suite and are calculated as follows;

BM = Book Equity(BE)/Market Value of Equity(mcap)

Data is supplied for 1962 of the banks in our sample.

Loans-to-Deposits (LD)
Both loan and deposit data is retrieved from the call report data in the BHC section of the Bank Regulatory database. The following items are used to calculate the loans-to-deposit ratio.

LD = Total loans and leases (BHCK2122)/[Total non-transaction savings deposits (BHCB389) + Total demand deposits (BHCB2210)]

Data is supplied for 1164 of the banks in our sample.

Loans-to-Total-Assets (LAT)

Loan and total assets data is retrieved from the call report data in the BHC section of the Bank Regulatory database. The loan to total asset ratio is computed as follows:

LAT = Total loans and leases (BHCK2122) / Total assets (BHCK2170)

Data is supplied for 1164 of the banks in our sample.

Maturity Gap (GAP)

For the maturity gap we use call report data from the RCON series in the Bank Regulatory database. The following assets and liabilities are used when calculating the maturity gap.

Assets:

RCONA549–554, RCONA555–562, RCONA570–575, RCONA564–569

Liabilities:

RCON6810, RCON0352, RCON2215, RCONA579–582, RCONA584–587

Average Maturity Period:

Following English (2014) we assign each item a midpoint value in months for its repricing period. For example, items with a maturity of 3.5 years are assigned 48 months etc. Some items do not have a repricing time, for example money market deposit, transaction accounts and non-transaction savings; these are thus assigned 0 months. For further details of how average repricing time is assigned see English (2014).

The maturity gap is calculated by taking the difference between the average repricing period of assets and liabilities. We multiply each item with its corresponding average repricing time. And then sum the products of the assets side and divide them by the total sum of the 26 asset items to get the average repricing time of the assets side. The same method is applied to the 11 items on the liabilities side.

$$\text{GAP} = (\Sigma A_i \cdot m_i^A)/\Sigma A_i - (\Sigma L_i \cdot m_i^L)/\Sigma L_i$$

Where A_i is asset item i, m_i^A the average repricing period for asset item i, L_i and m_i^L is the corresponding values for liabilities.

Data is supplied for 117 of the banks in our sample.

Income Gap (IGAP)

The income gap is the difference between the dollar amount of the bank's assets that re-price or mature within a year and the dollar amount of liabilities that re-price or mature within a year, normalized by total assets. These balance sheet items are found in the BHC section of the Bank Regulatory database.

IGAP = ((BHCK3197 - (BHCK3298 + BHCK3409 + BHCK3408 + BHCK3296))/BHCK2170)

Data is supplied for 1128 of the banks in our sample.

Net Profit Margin (NPM)

This is a measure reported in the Financial Ratios Suite supplied by WRDS.

NPM = Income Before Extraordinary Items (IB) /Total Sales (sale)

Data is supplied for 1924 of the banks in our sample.

Derivatives Ratio (DR)

Data on derivatives is taken from the BHC section of the Bank Regulatory database. It is calculated as follows;

DR = [Total gross notional amount of interest rate derivatives held for purposes other than trading(BHCK8725 + Contracts not marked to the market(BHCK8729)]/Total assets(BHCK2170)

Data is supplied for 1053 of the banks in our sample.