Modeling Variation in U.S. Bank Holding Companies' Net Interest Margins

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August 1, 2016

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Abstract

This study explores variation in US bank holding companies' (BHCs) net interest margins (NIMs) and the effects of interest rate risk exposure on NIMs. Interest rate risk (IRR) is intrinsic in maturity transformation and financial intermediation as banks take on short-term liabilities in the form of deposits and create assets in the form of loans with longer maturities and different repricing profiles. Accordingly, interest rate risk is necessary for bank holding companies (BHCs) to be profitable in financial intermediation, and net interest margins are chosen as a variable of interest because they are an isolated measure of bank' profitability from interest earning assets. Naturally, BHCs employ maturity pairing and derivative hedging to mitigate IRR and ultimately increase and smooth earnings. Synthesizing banks' balance sheet and income statement data, macroeconomic variables, credit conditions, and interest rate environment variables, this study hopes to expand on existing work by providing insight on the determinants of NIMs as well as interest rate derivatives' efficacy in increasing and stabilizing net interest margins. The models presented establish links between long term rate exposure, risk-averse capital positions, and increased margins. Additionally, the models suggest that banks earn smaller spreads (NIMs) in higher interest rate environments but benefit from steeper yield curves.

Keywords: Net Interest Margins, Interest Rate Risk, Depository Institutions, US Commercial Banking, Interest Rate Derivatives

JEL Classification: G20, G21, E44

Acknowledgements

I would like to extend the sincerest gratitude to my thesis advisor, Dr. Mary Beth Fisher, and my seminar advisor, Dr. Kent Kimbrough. Most importantly, I would like to thank my parents, Jordan and Christy Dorchuck, for their unconditional love and support.

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1 Introduction

This study will attempt to explain variation of US bank holding companies' (BHC) net interest margins (NIMS) across a sample of bank holding companies over the time period 2000-2014. Net interest margins (NIMs) are defined as the difference between interest income and interest expense weighted by the BHC's total interest earning earnings assets. The focus on interest rate margins isolates a core function of the BHCs (taking deposits and lending money) that is heavily dependent on interest rate risk exposure. Additionally, interest margins provide insight into the macroeconomy as the Federal Reserve cites bank net interest margins as a driver of loan growth and an indicator of health and stability in both the credit markets and the banking industry.[1] NIMs are a cost of financial intermediation for consumers and corporates, and lower costs (reflected by NIMs) benefit consumers and corporates and also reflect efficiency and competition in the banking industry. Moreover, studying risk positions in the banking sector, banks' responses to changes in market rates of interest and the corresponding effects on earnings can have implications for macroprudential policy making such as regulation of bank capitalization.

Interest rate risk (IRR) is a crucial risk faced by the commercial banking sector and can have a substantial impact on earnings. The most significant type of interest rate risk is repricing risk, defined as the risk that changes in interest rates or differences in maturities may affect the interest spread between assets and liabilities which in turn affect cash flows and timing of investment (Beets, 2004; FFEIC,

[1]Federal Reserve Council and Board of Governors. Record of Meeting. 2015, February 6.

2016). Additionally, interest rate risk poses a threat to the valuations of assets and liabilities on BHC's balances sheets, which can have substantial effects on banks with large trading businesses. Ultimately, the repricing risk of bank holding companies is reflected in earnings and balance sheet valuations. Logically, banks seek to mitigate IRR using a variety of strategies. Organically hedging interest rate risk, as it applies to the general corporation, is defined as matching interest rate exposure of assets with interest rate exposure of liabilities to improve consistency of earnings (Faulkender, 2006). For BHCs, this "organic" hedging strategy applies maturity gap analysis, and matching value of assets with a given maturity or repricing profile of assets with liabilities of a similar maturity or repricing profile. Maturity gaps (GAPs) are defined as the difference between the value of assets and liabilities with the same maturities, weighted by the total value of assets for the given maturity (Flannery & James, 1984). As this widens, in either direction, the BHC will be more exposed to risk associated with movements in interest rates for the given maturity profile (Flannery & James, 1984). Seeking to match assets and liability values for a given maturity "immunizes" the spread between earnings and expenses from movements in interest rates.

When managing interest rate risk, banks take into account movements in interest rates and term structures (the differences in interest rates with different maturities) and take positions reflected in short term and long term maturity gaps. Banks either seek to hedge current rate exposure or take active positions in IRR exposure based on projections and forecasts about the direction of interest rates. In addition to traditional, organic maturity GAP hedging to mitigate repricing risk, banks enter into interest rate derivative contracts to alter IRR exposure profiles. Accordingly, there are two ways in which banks hedge or take an active position in interest rate risk: altering maturity gaps on their balance sheets, using asset and liability management to reflect their beliefs in the interest rate environment, or entering into derivative contracts to "synthetically" alter IRR exposure.

The most common type of interest rate derivative used by bank holding companies is the interest rate swap. Interest rate swaps are a type of interest rate derivative in which two parties agree to "swap" payments for a specified duration of time. The most common interest rate swap involves one party agreeing to pay a fixed rate while the other agrees to pay a floating rate based around a market rate of interest, most commonly LIBOR. In practice, a bank may own an asset with a floating rate of interest and enter into a swap agreement as a floating rate payer, thus paying a floating rate of interest and receiving a fixed rate of interest. Furthermore, banks also hold interest rate futures and forward contracts, which are similar derivative contracts that set interest rates earnings (payments) for a specified period of time (Beets, 2004).

This paper will attempt to synthesize what is already known about the use of derivatives and maturity matching to hedge interest rate risk to quantify the effectiveness of interest rate derivatives as a tool to increase and stabilize NIMs for U.S. BHCs. An effective model will incorporate measurements of banks' IRR exposure using maturity profiles, interest rate derivative holdings, credit risk, capitalization, macroeconomic conditions, and the interest rate environment, including rate volatility to describe variation in NIMs.

This study attempts to distinguish itself from existing literature by the scope of the data and inclusion of interest rate derivatives. Existing literature has not explored this effect of interest rate hedging on NIMs with post-crisis data, and I am interested in exploring how the post-crisis interest rate and macro environments have influenced banks' profitability. In an unprecedented macroeconomic environment and drastically changing banking and regulatory landscape, it will be informative to see if empirical models of IRR exposure and bank profitability are consistent with models in previous literature. For example, higher post crisis capitalization (ratio of equity to total assets) and liquidity requirements for banks may incentive banks to hedge interest rate risk with less capital-intensive methods such as interest rate swaps as opposed to matching balance sheet assets and liabilities. In addition to novel regulation of the banking industry and macroeconomic policy making, the rapid consolidation of the industry that occurred during and after the crisis has undoubtedly changed the market structure of the banking industry which will affect empirical models for NIMs.

2 Literature Review

Existing literature on interest rate risk management, hedging strategies, and empirical models for NIMs will be discussed to frame the theory behind the empirical models. First, the literature review will explore the existing literature on bank interest rate risk management, such as determinants of interest rate risk for BHCs and the value of derivatives in bank interest rate risk management. This portion of the literature review will introduce theories in banking, such as financial intermediation, that compose some of the theoretical framework for the empirical model later presented. Next, previous academic studies on determinants of net interest rate margins, and profitability for commercial banks will be summarized. This portion will emphasize the results of the empirical models and what these results can lend to the formation and interpretation of this paper's empirical model. The four types of IRR are given below, taken from an FDIC report on interest rate risk.[1]

1. Repricing Risk

    - *"Reflects the possibility that assets and liabilities will reprice at different times or amounts and negatively affect an institution's earnings, capital, or general financial condition" (FDIC, 2015).*

2. Basis Risk

[1]Federal Deposit Insurance Corporation. (2015, March). *Risk Management Manual of Examination Policies: Sensitivity to Market Risk*

- *"The risk that different market indices will not move in perfect or predictable correlation" (FDIC, 2015).*

3. Yield Curve Risk

    - *"Risk that reflects exposure to unanticipated changes in the shape or slope of the yield curve. It occurs when assets and funding sources are linked to similar indices with different maturities (FDIC, 2015).*

4. Option Risk

    - *"The risk that a financial instrument's cash flows (timing or amount) can change at the exercise of the option holder, who may be motivated to do so by changes in market interest rates" (FDIC, 2015).*

One study approaches IRR from a broad corporate perspective, defining IRR liability exposure as the spread between long and short term bonds issued by the corporation (Faulkender, 2005). Consequently, the shape of the yield curve is a key determinant of corporate debt issuance for the firms in the dataset, indicating that firm are not hedging, based on matching interest rate exposure of assets and liabilities of similar maturities, but rather taking active positions in interest rate management to reduce cost of capital based on interest rate expectations (Faulkender, 2005). Other studies identify asymmetric information and credit quality expectations as factors within that influence a firm's participation in the fixed income market, presenting opportunities for the firms (Titman, 1993). For example, firms that expect their rating to improve would rather borrow short term and then swap for a fixed rate obligation. Both studies suggests that firms actively take on IRR exposure.

A variety of other studies expand on IRR research and apply theory to banks specifically. "Bank Risk Exposure" a working paper studying the structure of interest rate and credit risk for a large sample of BHCs. Credit and interest rate risk factors are "orthogonalized", indicating linear independence such that variation in overall risk is explained by distinct, uncorrelated measures of interest rate risk and credit risk. The former is captured by returns on long term, safe bond portfolios which decline in value with increases in interest rates while the latter is explained by returns on high yield bond portfolios. A positive IRR risk factor corresponds to long position in the safe bond portfolio which loses value with increases in the yield curve and market rates of interest. These two orthogonalized risk factors are included in regressions on returns of securities with different maturity and risk profiles that make up a large portion of BHCs' portfolios. Using the risk factor regressions, risk profiles are compared for the banking sector as a whole and across security types. The regressions identify sources of variation in returns for securities, noting as credit quality deteriorates, less variation is explained by interest rate risk, implying a negative interaction between credit and interest rate risk (Begenau, Piazzesi, & Schneider, 2015). The authors identify a stark contrast in interest rate risk profiles between the two types of banks as market makers oversaw huge increases in interest rate risk exposure during the 2000s and continued to maintain large positions in interest rate risk exposure after 2008 even though all banks decreased their credit risk substantially (Begenau, Piazzesi, & Schneider, 2015).

A number of studies explore the theory behind the usage of swaps by banks. "The Use of Interest Rate Swaps by Commercial Banks", explores the determinants of the use of interest rate swaps by commercial banks by regressing the notional value of swaps used by a given bank against a selection of bank descriptive variables. Manipulating data on U.S. banks with assets larger than $5 billion from 2001, the study finds that larger banks, as measured by the value of their assets, are more intensive users of interest rate swaps, and banks with higher quality assets on their balance sheets are also more likely to employ interest rate swaps in hedging interest rate risk (Boukrami, 2001). Additionally, banks with higher capitalization are more likely employ the use of swaps (Boukrami, 2001). The study establishes a link between sound capital positions and bank size and the use of interest rate swaps but does not find a significant link between interest rate risk exposure (measured as the ratio of net interest income to total income) with the use of interest rate swaps (Boukrami, 2001). The author also offers insight into the limitations in maturity gap analysis, stating that maturity gap analysis leaves out the effect of interest rate derivatives on interest rate exposure. Another study accounts for both on-balance sheet risk management and off-balance sheet management in the study of interest rate risk, and finds that BHCs that employ interest rate derivatives keep both their maturity GAPs and lending volume constant during interest rate shocks, implying that the use of derivatives can bring stability to earnings for banks during monetary policy fluctuations (Purnanandam, 2005). This is integral research for my paper as it explores links between derivative usage, interest rate shocks, and lending volume, the obvious driver of interest rate earnings.

Two significant papers present models for bank equity performance using IRR and GAP analysis. Determinants of equity valuations should lend insight into margin variation as equity valuations mirror earnings performance. "The Effect of Interest Rate Changes on the Common Stock Returns of Financial Institutions", written in 1984 looks at the role of interest rate risk and banks' hedging on common stock returns for commercial banks and savings and loans corporations. First, the authors regress common stock returns against unexpected changes in Government National Mortgage 8 percent certificates, changes in 7-year US Treasury bond yields, and the weekly return on the 1-year US Treasury bills. These variables for unexpected rises in interest rates are significantly negatively correlated with the return of the bank stocks

(Fannery & James, 1984). The authors also explore the maturity composition's effect on the returns of common stock. A variable is created for the net position of short-term assets and liabilities and weighted over the market value of the bank's common stock over that period (Flannery & James, 1984). The model indicates that fewer short assets than liabilities create more interest rate risk, and banks with this risk exposure see their share prices decline with a rise in interest rates (Flannery & James, 1984).

"Interest Rate Risk and Bank Equity Valuations" expands on the themes and factors scrutinized in the previous paper but focuses more of the effect of FOMC announcements on interest rates from 1997 to 2007 on bank equity valuations (English, Van den Huevel & Zarajsek, 2012). It also adds tests the effect of interest rate derivatives in mitigating the effects of interest rate shocks on equity performance. The authors find that swap exposure is not statistically significant in determining the bank equity's reaction to interest rate shocks across all banks but note the limitation inherent in simply using the value of swap notionals as an explanatory variable because it does not adequately capture the position on interest rates, just the contract size (English, Van den Huevel & Zarajsek, 2012). However, the authors' model does suggest, using quantile regression methods, that heavy exposure to interest rate risk accentuates the negative effect of interest rate surprises on equity valuation (English, Van den Huevel & Zarajsek, 2012).

A paper from the Atlanta Federal Reserve explores a number of relevant questions surrounding the dynamics of net interest margins in US commercial banking. The author examines the lag between the decline of interest rates and the decline in net interest margins and how net interest margins were able to rise despite interest rate decreases in the early 2000s (Anderson, 2012). The paper also presents the Dupont method which derives NIMS from the yield/cost spread, adding the gain or loss from net interest positions which is represented graphically in this paper's theoretical framework (Anderson, 2012). Therefore, Anderson provides a link between repricing risk (in the form of gains or losses on interest rate positions) and NIMs. Anderson sheds light on the importance of NIMs in the greater economic framework and banking sector. The author notes how increased net interest margins can be a cushion for lower earnings in a low rate interest rate environment, but the compression of NIMS over time can pose a threat to commercial banks and their ability to set aside capital to account for default risk and losses from operations and increasing costs (Anderson, 2012). Another study (Saunders & Schumacher, 2000) views NIMs as a cost of financial intermediation for consumers and highlights the public policy implications that stem from an understanding the determinants of NIMs (Saunders & Schumacher, 2000). The authors pose an example: if interest rate volatility is significantly positively associated with NIMs, then macroeconomic policy makers should shift focus towards lowering interest rate volatility to help lower costs of financial intermediation (Saunders, & Schumacher, 2000).

Previous empirical studies on NIMs will set the framework for the empirical models in this paper. Ho and Saunders in "Determinants of Interest Rate Margins" (1981) developed the "dealership" model, an intuitive microeconomic model to determine pure interest rate margins in a period ranging from 1976- 1979 using quarterly balance sheet data for 53 banks. The explanatory variables used are market structure, managerial risk aversion, interest rate volatility (measured quarterly over weekly bond rates), and average transaction size over the given period (Ho & Saunders, 1981). The model explains a significant amount of variability in interest rate margins and identifies consistently statistically significant variables in the model with interest rate volatility having a significant positive effect on NIMs (Ho & Saunders, 1981). Saunders and Schumacher in their international study, model

NIMs for banks in a number of countries including the United States using dummy variables to control for differences in regulation and market structure. The authors explore regulatory environments, reserve requirements and capital held (as opportunity costs for not lending out deposits) and macro factors such as interest rate volatility as predictors of NIMs (Saunders & Schumacher, 2000). The authors note that an increase in interest rate volatility will increase NIMs on average, which is contrary to the results for interest rate changes on equity valuations, but consistent with the theory of the dealership model (Saunders & Schumacher, 2000). Another empirical NIMs study finds support for the hypothesis that banks with higher levels of credit and interest rate risk are compensated with higher margins for bearing more risk (Angbazo, 1997). Moreover, the study finds a positive association with capital and management quality (proxied by operation costs) and NIMs (Angbazo, 1997). Angbazo's study also finds that larger banks are more sensitive to IRR, and smaller banks are more sensitive to default risk (Angbazo, 1997). Lastly, Aliaga-Diaz and Olivero find significant evidence for NIMs as a consistently countercyclical variable controlling for bank market concentration, monetary policy, capital structure, and interest rate risk (Aliaga-Diaz & Olivero, 2011). The studies presented provide an excellent framework for modeling net interest margins and a great deal of theory to understand and interpret the results of the models in this paper.

3 Theoretical Framework

This paper explores a number of underlying economic theories around interest rate risk and financial intermediation. Additionally, the paper will compare results from the subsequent economic models with economic theory and models for net interest margins. Presented below are underlying theories behind and methodologies for calculating NIMs and maturity GAPs.

3.1 Interest Rate Risk

This paper's focus on building a model for the determinants of NIMs isolates effects of interest rate risk (using maturity gap measurements) on bank earnings. Simply put, how does holding interest rate risk affect banking profitability, controlling for macroeconomic, credit risk, and bank capital positions? Maturity gap (GAP) analysis is one method of identifying and maturity mismatches, which in turn are the root of repricing risk on a bank's balance sheet. Equation 3.1 describes the simplest measurement for maturity gap ratios.

$$GAP_{j,t} = \frac{\sum Avg.EarningAssets_{j,t} - Avg.Int.BearingLiabilities_{j,t}}{Avg.EarningAssets_t} \quad (3.1)$$

An integral idea behind financial intermediation is the idea that increases in interest rate risk, measured in maturity gaps, on a bank's balance sheet should enhance profits as banks are compensated for bearing risk as asset transformers, taking liabilities with short term maturities and repricing profiles and creating and holding assets with longer maturities. Repricing risk is reflected in earnings; “By mismatching the duration of assets and liabilities the bank subjects itself to additional interest rate risk commensurate with higher expected returns” (Bharati, Nanisetty, & So, 2006). This paper will empirically test this theory by modelling the effects of interest rate risk on bank earnings, controlling for other significant factors.

The paper will draw connections with IRR and maturity transformation and the fundamental theory behind the use of interest rate swaps by banks and corporations. Banks, like corporations, can take positions on interest rate risk or seek to insulate earnings from interest rate risk (Chernenko & Faulkender, 2005). The effects of these interest rate risk positions and the corresponding hedging positions on profitability will be reflected in the NIMs variable. One study on derivative usage by commercial banks posits, ”Banks face a high degree of interest rate risks, and, therefore, hedging decisions have a first-order impact on their performance” (Chernenko & Faulkender). The empirical models aim to isolate these effects and the interaction between GAP measurements of IRR and derivative exposure.

3.2 Net Interest Margin Theory

There are a a two different methods to calculate NIMs presented in this section to provide a sound background on the theory behind the composition of the variable. The Anderson-Dupont Composition (figure 3.1) is equal to the simple equation given in equation 3.2, which is the simplest calculation for NIMs.

$$NIMs_{i,t} = \frac{InterestIncome_{i,t} - InterestExpense_{i,t}}{AverageEarningAssets_{i,t}} \tag{3.2}$$

Presented in Figure 3.1 is the formula proposed as the Anderson-Dupont de-

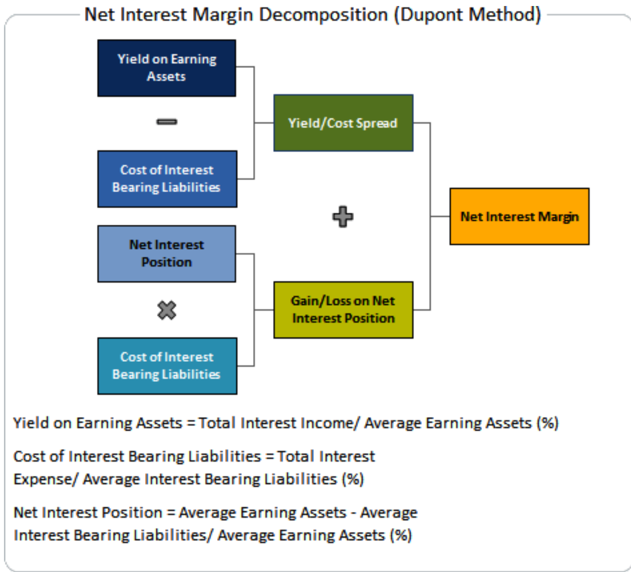

Figure 3.1: Anderson-Dupont Decomposition Method

compostion for NIMs (Anderson, 2013). It relates the bank's net interest position to the yield-cost spread. This breakdown of NIMs directly links IRR exposure (net interest position), a significant link between the two pillars of this paper's theoretical framework.

As mentioned in the literature review, economists have presented models to determine the market spread between interest earnings and interest expenses for banks. Ho and Saunders present their model for NIMs, commonly referred to as the "dealership model" in which each bank seeks to maximize their gains on wealth subject to unexpected asymmetries in arrival of supply of deposits and demands of loans (Ho & Saunders, 1981). Allen (1988) and Angbazo (1996) expand on the dealership model, positing that banks set the rates on loans and deposits according to risk tolerance (Saunders & Schumacher, 2000; Allen, 1988; Angbazo, 1997). Equations 3.3 through 3.5 define the pure spread outlined in Ho and Saunders (1981).

$$R_L = (r + b) \tag{3.3}$$

$$R_D = (r - a) \tag{3.4}$$

$$R_L - R_D = (a + b) \tag{3.5}$$

where:

r is the expected market risk free rate

R_L is the rate set on loans; R_D is the rate set on deposits

a & b are the fees charged to provide immediacy and bear interest rate risk

The derivation of the banks utility maximizing functions on current portfolio of assets and the inflow of investment over the period yields the spread between the two rates as equation 3.6

$$s = a + b = \frac{\alpha}{\beta} + \frac{1}{2} R \sigma_i^2 Q \tag{3.6}$$

where:

$\frac{\alpha}{\beta}$ represents the bank's risk neutral spread and is the ratio of the intercept (α) to the slope (β) of the symmetric loan and deposit arrival function. "A large α and small β will result in a large spread thus if a bank faces relatively inelastic demand, then it will be able to exercise monopoly power (and earn a producer's rent) by demanding a greater spread than it could if banking markets were competitive" (Saunders & Schumacher, 2000). In sum this ratio is a measure of competition in the banking industry, meant to capture the degree of producer rent or monopoly power present in the measure of NIMs

R is the bank's coefficient for risk aversion

σ^2 *is the variance of the interest rates on loans and deposits*

Q *is the quantity of bank transactions*

Previous models for NIM determinants provide the economic theory behind net interest margins econometric models, building from the the "dealership" model for pure spreads. The first model for bank NIMs from Ho and Saunders posit that firm level margins are a function of the pure spread, implicit interest payments (non-interest payments), reserve holdings, and default risk, and find that non-interest expenses are significant (Ho & Saunders, 1981). Bank level NIMs are then regressed against interest rate volatility, which is positively associated with NIMs (Ho & Saunders, 1981). Saunders and Schumacher expand on this, adding required capital for credit risk exposure into the list of determinants (Saunders & Schumacher, 2000). Next, Angbazo deviates from the dealership model, noting that the dealership model does not explain *why* certain banks take on more risk than others (Angbazo, 1997). The model adds interest rate risk and the interaction between interest rate and credit risk variables (Angbazo, 1997). Lastly, Aliaga-Diaz and Olivero model NIMs as consistently counter cyclical, even in the event of monetary policy shocks (Aliaga-Diaz & Olivero, 2011).

4 Data

4.1 Data Sources and Descriptions

The data is compiled from a variety of sources, mainly The Federal Reserve Bank of St. Louis' macroeconomic database, the Bloomberg Terminal's extensive database on financial markets, and the Wharton Data Services' aggregation of US bank holding companies' Federal Reserve Call Report data. The Federal Reserve requires US commercial banks with over $500 million in total consolidated assets to disclose on a quarterly basis interest bearing assets and liabilities as well as notional values of derivative and market values of trading derivative positions (Begenau, Piazzesi, & Schneider, 2015). This data are found in quarterly call reports on the Federal Financial Institutions Examination Council (FFIEC) website and is reported quarterly in FR-Y-9C reports, reports filed to regulators to provide comprehensive balance sheet and income statement information. These reports are consolidated and aggregated in the Wharton Research Data Services website. The initial scope of the dataset includes all BHCs that file call reports on a quarterly basis since 2000, but is then subsetted to include only those bank holding consolidated assets greater than $100 billion and a consistent set of observations in the dataset.

Consolidation in the commercial banking industry has defined the post-crisis environment. Now, the largest banks in the industry own significantly more interest earning assets; the Federal Reserve Bank of St. Louis study states that as of June 2014, the four largest commercial banks control 44% of commercial bank assets compared to 39% in 2006 (Wheelock, & Wilson, 2015). Furthermore, there are fewer banks now than there were before the crisis, and the Federal Reserve Bank of Richmond cites a decline of 14% in the number of independent commercial banks in the US between 2007 and 2013 (McCord, Simpson Prescott, & Sablik, 2015). The changing scale of the industry may influence the usage of interest rate derivatives, as more assets owned by the larger banks who are more intensive users of IR derivatives (Boukrami, 2001). Consolidation in the industry is somewhat accounted for in the FR-Y-9C reports. If a particular BHC makes an acquisition of a BHC in a given quarter, the BHC reports income statement data for "predecessor institutions" as well as the value of assets acquired under an auxiliary form. However, further information on maturity, specific interest earnings and expenses, and risk profiles of the acquired assets are not included, posing a limitation in the data and the bank call reports. But dummy variables for an acquisition, and the value of acquisition by asset sizes are included in the final model.

The maturity profiles for the assets and liabilities included in the banks' call reports are broken down into 2 "buckets", based on the maturity and repricing profiles of the assets and liabilities. The short term "bucket" includes assets that mature or reprice within one year based on movements in interest rates while the long term " bucket" includes those that mature in a year or later or do not change payments of interest based on market interest rate changes. The assets and liabilities in each "bucket" will be "matched up" and weighted by asset values in maturity gap analysis.

The dataset consisting of bank specific variables will take data on a quarterly interval for the 18 BHCs included in the dataset, starting in the first quarter of 2000 and continuing to the fourth quarter of 2014, containing a total of 60 quarters and includes a total of 1044 observations. The small size of the dataset is one problematic issue with the panel data analysis, but it is unfortunately a necessary shortcoming of the analysis for two reasons. First, the declining number of BHCs in the US limits the number of BHCs that file reports across the entire time series. Secondly, inclusion of smaller BHCs will skews the analysis away from the larger BHCs that control the majority of assets in the financial system, take on more interest rate risk, and employ derivative hedging more frequently.

4.2 Descriptive Statistics

4.2.1 Macroeconomic Variables

The descriptive statistics on macroeconomic variables provide a great deal of insight on how the macro variables will play into the regression models. First, the LIBOR rates and 10 year U.S. treasury rates are slightly positively correlated with NIMs, supporting to a degree claims that higher interest rates are good for bank profitability. Conversely, the 10 and 2 year treasuries spread rate is marginally negatively correlated with NIMs, contesting claims that a steeper yield curve leads to higher bank earnings. The BAML credit spread variable is negatively correlated with NIMS, suggesting that bond market perceptions of credit risk decrease NIMs. Inflation, measured by the CPI variable, is negatively correlated as well, suggesting that changes in prices negatively impact bank earnings on the margin. Finally, and perhaps most importantly, there is a strong negative correlation between US GDP and US NIMs, indicating that NIMs could be a countercyclical macroeconomic variable. This is supported by the negative correlation between NIMs and the S&P 500, a broad measure of the US stock market performance, often used as a proxy for economic performance. However, it is important to note that the data is an

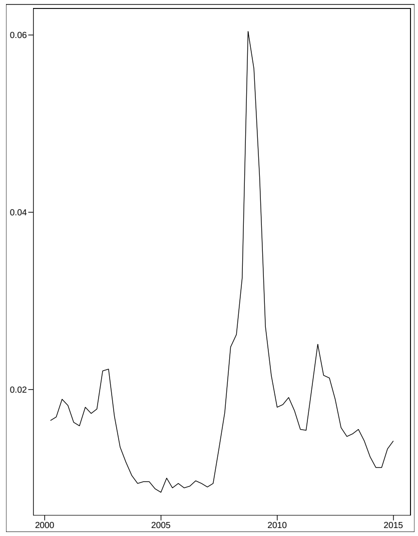

Figure 4.1: Credit Spread Values

aggregate of all insured U.S. commercial banks.

- *Corporate Credit Spreads* the Bank of America Merrill Lynch U.S. Corporate Master Option-Adjusted Spread tracks the difference in spread between a weighted collection of investment grade bonds (rated BBB or higher) and a corresponding spot treasury curve rate to quantify perceived difference in default risk between corporate credit and U.S. government debt, which is considered risk free. This is a proxy for market perceptions of default risk in credit markets but only includes bonds. 4.1 graphs this measure of corporate investment grade bond yield spreads on a daily basis over the time frame of the dataset.

- *Commercial and Industrial Loan Volume* Using the St. Louis Federal Reserve's data on commercial and industry loan volume, this explanatory variable will quantify overall commercial banking lending activity in the US in the quarter. Figure 4.2 shows the total loan volume increasing overtime, which consequently

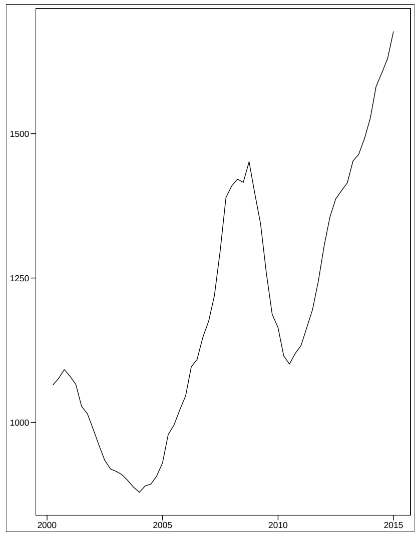

Figure 4.2: U.S. Commercial & Industrial Lending Volume ($ billion)

is negatively correlated with NIMs over the dataset.

- *Interest Rates* Quarterly averages of effective Federal Funds rate, the 1-month LIBOR, 3-month LIBOR, 6-month LIBOR, 12-month LIBOR, and 10-year U.S. Treasuries are included in the models. However, to counter multicolinearity in the models, principal component analysis is performed on the interest rates to isolate variation and remove correlation. One would assume that higher rates lead to higher profits for banks, as banks charge more on loans. However, as noted in previous studies, increases in interest rates have two conflicting effects: 1) Improving earnings on future loans and 2) discounting the value of outstanding long term positions.[1] Additionally, previous studies have found interest rates to be negatively associated with equity values (Flannery, & James, 1984).

[1] *The Economist*, "Aiming for the Net", June 2015

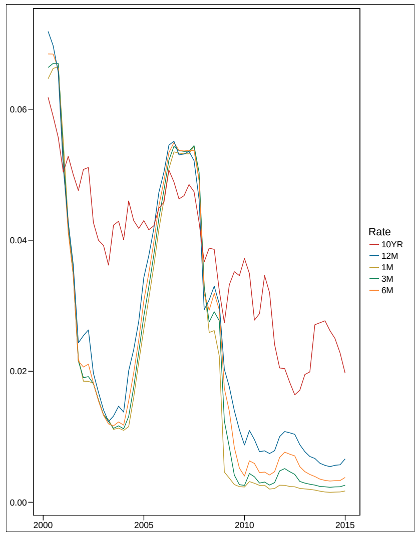

Figure 4.3: Interest Rates Over Selected Time Period

- *Interest Rate Volatility* The models include 90 day measures of interest rate volatility (standard deviation) for the 1,3,6, and 12 month LIBOR rates as well as the 5,10, and 30 year U.S. treasuries. Additionally, PCA will be performed to correct for multicolinearity. Past studies have identified IR volatility as especially positively significant in the determination of NIMs, and interest rate volatility is positively linearly related to the pure spread in the dealership model (Ho & Saunders,1981). Moreover, banks price the macroeconomic risk of interest rate volatility into their intermediation fees (in the form of higher rates on loans), as shown in one particular study (Entrop, Memmel, Ruprecht, & Wilkens 2015). Interest rate volatility is of particular interest in this study because of its central role in previous NIMs models, such as the dealership model, and because of its association with interest rate risk.

- *Term Structure/ Yield Curve* The difference in spreads on 10-year and 2-year US Treasuries will be used as a proxy for the shape of the yield curve. A "normal" shaped yield curve, indicated by a positive value in the difference of 10-year and 2-year treasuries, should favor bank profitability based on fundamental financial intermediation theory as banks take on short term liabilities and transform them into long term assets which have higher yields than short term liabilities in normal yield curve environments (Entrop, Memmel, Ruprecht, & Wilkens 2015). One paper refers to this as conventional wisdom behind the link between term structures and NIMs (English, W., Van den Heuvel, S., Zakrajsek, E. 2012). Taking into account theory on maturity transformation, I expect that NIMS will be correlated with a positive spread value between the 10 and 2 year U.S. treasury rates.

- *LIBOR Swaps* Prices for 1,5, and 10 year LIBOR swap contracts will be included in the model to see how prices of swaps effect NIMs and interact with interest risk variables. The underlying pricing methodology of an interest rate swap sets each party's discounted expected cash flows equal to one another at the start date of the contract. One method for valuation uses discount rates that are derived from implied forward rates to value the cash flows on each side of the swap (Cusatis, 2007, p. 3). The underlying theory in using forward rates in pricing interest rate swaps is the "Pure Expectations Hypothesis", meaning that "expected future short-term rates are equal to forward rates implied in the yield curve" (Cusatis, 2007, p. 8). Therefore, swap rates give information about expectations of interest rates and volatility.

- *GDP Growth* Aliaga-Diaz and Olivero present a case that NIMs are a countercyclical economic variable, indicating that NIMS are negatively correlated with increases in macroeconomic output (Aliaga-Diaz, & Olivero, 2011). Supporting this, is the high negative correlation between GDP and NIMs, shown in table

4.1 Additionally, the inclusion of GDP will help in controlling for measures of general economic performance over the length of the dataset.

- *Inflation* Previous studies suggest a positive link between NIMs and inflation rates, noting that inflation poses informational asymmetries in financial markets, leading to higher costs of financial intermediation (Aliaga-Diaz, & Olivero 2005). Moreover, Saunders and Schumacher present a link interest rate volatility and inflation and consequently inflation and NIMs (Saunders & Schumacher, 2000) The data for inflation are taken from the FRED database and measured in consumer price index units with 1982-1984 as the base year (= 100).

- *S&P 500 Quarterly Index Value* S&P value is used as an additional proxy for economic performance. One could intuitively predict stock market indices to be positively correlated with bank profitability as higher, more stable corporate earnings, if reflected in the stock market, could indicate lesser loan defaults and therefore higher bank profitability.

4.2.2 Panel Data Variables

The term, "panel data", refers to the bank-specific datapoints taken from the Wharton Data Services aggregation of bank holding companies' FR-Y-9C. Previous studies have identified a number of bank specific variables as statistically significant determinants of net interest margins and bank equity values on other samples of commercial banks and lending companies. The model in this study will retest variables presented in other studies and also test measures of interest rate exposure and interest rate derivative holdings for significance. Merger Value is included in call reports for acquisitions over the period of the dataset. If an acquisition exceeding

$10 billion in asset value or value greater than 5% of the acquirer's assets, the BHC will include the average total asset value for the predecessor institution in its fourth quarter report [2]. This value is included in the dataset as *Merger Value*.

- *Net Interest Margins* One of the largest limitations of the Wharton Call Report dataset is the exclusion of the "average earning assets value" for the most of the dataset. As a result, "average total assets" is substituted in as the denominator of equation 3.2 which deflates the NIMs value for the dataset, which takes away from both the accuracy of the panel regression model and ability to draw comparisons with the macro model. However, the trend of declining NIMs for this proxy variable over the period is consistent with the trend for the aggregate NIMs value, as shown in figures 4.4 and 4.5, and thus the variation across time will be similar between the two dataset. Therefore, the direction and significance of the regression coefficients in the panel model should bear resemblance to the average coefficients in the macro model.

- *Maturity Gaps*: Call reports give a limited breakdown of interest bearing assets and liabilities for all banks dividing each into two repricing profiles (less than one year and greater than 1 year). The measures of maturity gaps for each BHC at the end of each quarter will be calculated as the difference between the assets and liabilities with the same maturity profiles and weighted over the total assets for the particular repricing profile. I expect both short term and long term GAP variables to be positively associated with NIMs as financial intermediation theory posits that banks are compensated for bearing interest rate risk. A small positive correlation between both GAPs and NIMs supports this intuition. Furthermore, since short term rates yield less in a normal rate

[2] Federal Reserve Instructions for Call Report Preparation, 2015

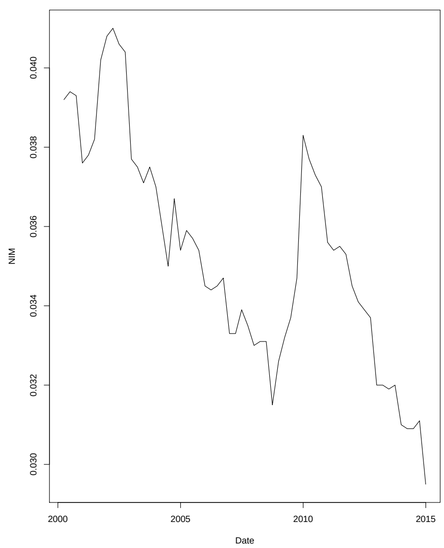

Figure 4.4: Macro NIMs

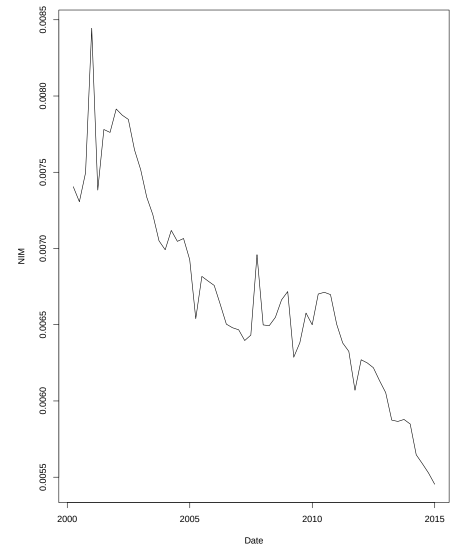

Figure 4.5: Call Report NIMs

environment, I expect the increases in NIMs from an increase in the short term GAP to be less than the effect of a LT GAP change. A larger difference between long term assets and liabilities will indicate a larger exposure to long term yields, which in normal term structure (yield curve) environments, will be more profitable than exposure to short term rates. Looking at table 4.2.2, we see on average, banks have a positive ST GAPs and negative LT GAPs, this indicates positive exposure to short term rates and negative exposure to LT rates. As GAPs represent the interest rate risk profiles of BHCs, special attention should be paid to how these variables interact with IR derivatives. Put simply, do the relationships between IR risk (GAPs) and NIMs change with the inclusion of IR derivative hedging? If these interaction terms are positive and significant then, the positive effect of taking on more interest rate risk is improved by derivative usage. If the interactions are negative, the increase (or decrease) in NIMs from IR rate exposure is lessened with greater IR risk, indicating that the hedging instruments and the BHC's IR risk exposure have conflicting (hedging) effects.

Moreover, the model results will also focus on interactions between GAPS and IR rates and volatility measurements. Similarly to the motivating questions behind interactions between hedging instruments and IR risk, how do the effects of interest rate changes and volatility on NIMs change as BHCs increase their interest rate exposure? Logically, these should move in tandem, as changes in rates should have larger effects on earnings based on IR rate exposure.

- *Net Interest Income / Total Net Income* Represents the proportion of bank earnings that are earned from bank intermediation (maturity transformation) and interest bearing assets relative to fee based earnings. Used as an additional proxy for interest rate risk in previous studies by Bourkami, it offers a broad, but less nuanced measure of the interest rate risk in the bank. This variable takes into account the effect of derivative hedging on interest rate risk, as earnings and expenses from derivatives are included in net interest earnings. On the other hand, maturity gaps cannot capture derivative hedging as they measure only on-balance sheet ratios (Bourkami, 2001).

- *Risk Weighted Assets* To monitor exposure to market risk, bank regulators require BHCs with significant trading businesses to report assets and off-balance sheet exposures, weighted according to the risk-profile of each asset and exposure. This measure of bank risk exposure is often used by bank regulators in gauging capital adequacy with respect to both size and risk. Risk weights of securities, loans, and derivative contracts range from 0% to up to 200%.[3] Risk

[3] Board of Governors of the Federal Reserve System. (2007, March)

weights are determined based on credit ratings, maturity profiles, and securitization positions, according to the Fed's guidelines. The face values (for assets) or notional values (for derivatives) are multiplied by their corresponding risk weights and summed to arrive at a total risk weighted asset (RWAs) value for the bank. The effects of RWAs on NIMs can be a challenge to interpret, as the measurement captures both size of positions and their corresponding risk profiles thus embedding effects of both risk and transaction size. Furthermore, both risk aversion and transaction size are included in pure spread models from Ho and Saunders (Ho & Saunders, 1981). The aggregate value of RWAs in the 18 bank dataset is shown in figure 4.6. The total RWAs increase over time, albeit with a small dip post-recession, while NIMs on the whole decreased steadily, suggesting, albeit weakly, that size and risk in the financial system may compress NIMs over the period. Additionally, there is a slight negative correlation between bank level NIMs, suggesting this link at a micro level as well.

- *Provision for Loan Lease Losses* BHCs include provisions for losses on loans and leases, also called loan loass reserves (LLR) in their respective call reports. This captures bank perceptions of credit risk present in each bank's loan portfolio. In aggregate, it can be viewed as an indicator of market credit conditions. However, this is a limited measurement of the individual bank's total credit risk because it does not account for credit risk in trading securities. The Federal Reserve Bank of Atlanta states that during and following the crisis, "the provision expenses many of these banks took to build loan loss reserves were substantial and a key negative driver of earnings growth" (Anderson, 2012). Loan loss provisions can suppress profitability in banks, as capital is set

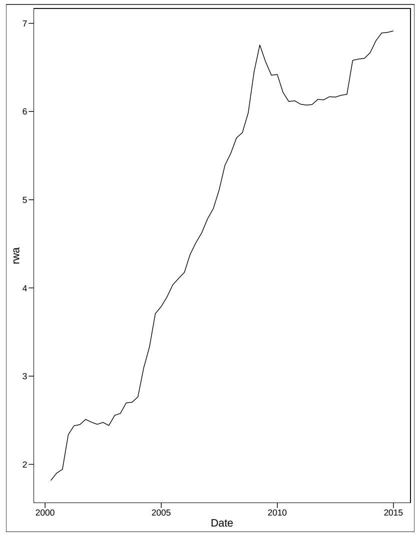

Figure 4.6: Total Risk Weighted Assets

aside in anticipation of loan defaults rather than lent out. Much like holding reserves and equity capital, there is an opportunity cost of holding LLR. This suggests a negative impact on profitability. Conversely, increases in LLR could indicate prudent credit risk management and held support earnings stability in periods of credit defaults. Additionally, previous research suggests that banks price the opportunity cost of capital into NIMs resulting in a positive association (Saunders, & Schumacher, 2000). Figure 4.7 gives an aggregate ratio for loan loss reserves tot total assets for US Commercial Banks, and the total loan loss provisions for the 18 bank dataset is given in 4.8.

- *Opportunity Cost of Reserves* This is measured as the sum of cash and reserve deposits with the Federal Reserve and other commercial banks. This is expected to have a negative effect on NIMs as more capital held in reserves leaves less for the bank to lend out as interest earning assets. This effect is confirmed by a previous studies (Angbazo, 1997; Saunders & Schumacher, 2000).

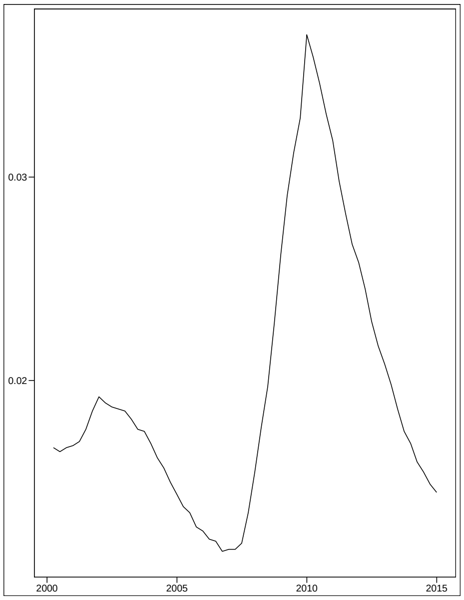

Figure 4.7: FRED Loan Loss Reserves

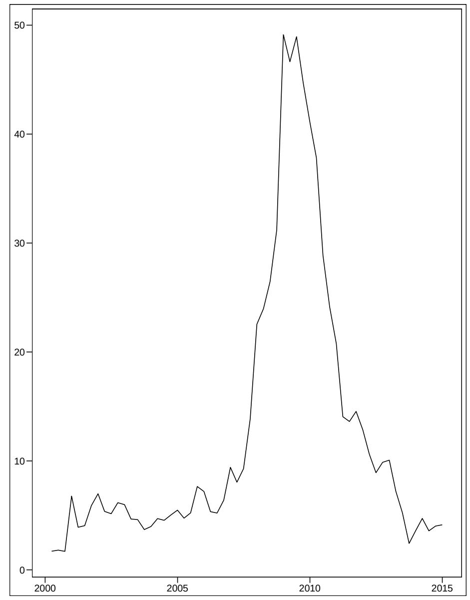

Figure 4.8: Call Report Loan Loss Provisions

The Federal Reserve stipulates that banks hold a percentage of their liabilities in the form of deposits at other commercial banks and the Federal Reserve. Much like the theory behind LLRs, one could predict reserves will have less of a negative impact on bank profitability since the Federal Reserve has begun to pay a rate of interest on reserves held at the Fed.

- *Bank Capitalization Ratios* In compliance with the Federal Reserve, Basel III and other bank regulations, banks must hold a certain amount of capital (in the form of equity) on their balance sheets to protect liability holders (depositors and creditors) in the event of substantial bank losses. In the past few years, and as a result of federal legislation, banks are required to hold more equity on their books to decrease their leverage ratios and therefore risk of insolvency.[4]

[4] Board of Governors of the Federal Reserve System, 2013

Included in the data are values for tier 1 capital, tier 2 capital, and total capital. Tier 1 capital, such as common equity and retained earnings, consists of capital that can absorb losses without obstructing normal operations while Tier 2 capital consists of broader, less reliable sources of capital such as loan loss reserves, subordinated debt, provisions of loan and lease losses, and revaluation reserves.[5] Regulators specify ratio requirements of the previous capital measures against average earning assets and average risk weighted assets. Research finds evidence that capitalization is correlated with profitability because it is expensive for banks to hold equity and banks price this into higher rates (Saunders & Schumacher, 1981; Angbazo, 1997) Higher capital ratios indicate more risk-aversion in credit markets by banks as surplus capital can absorb unexpected losses from credit defaults, asset devaluations, and unforeseen drops in earnings.

- *Interest Rate Swap Notional Values* The notional values represent the principal amounts for the theoretical fixed income security from which the swap derives its payments (Beets, 2004). Therefore, the notional amount of interest rate derivatives indicates the total amount of contracts in which a bank has entered. The call reports stipulate that banks specify between derivatives used for trading and those derivatives not used for trading. Those derivatives held for trading are recorded as part of the balance sheet. Both trading and not-for-trading derivatives will be included in the model. Consistent with ideas presented in previous literature, one would predict that larger notional values of swap contracts will help banks improve earnings as derivative usage allows banks to increase lending volume and hold less capital on its balance sheet

[5] Board of Governors of the Federal Reserve System, 2013

(Brewer, E., Jackson, William., & Moser, Peter, 2001). Angbazo (1997) finds that off balance sheet derivatives are associated with consistently higher margins as they facilitate a more diversified revenue stream (Angbazo, 1997). Of particular interest will be the interaction terms in the model between derivative values, the measures of interest rate risk, and the macro indicators of interest rate volatility. For example, a positive coefficient for the interaction between swap notional values and long term maturity gaps indicate that banks' positions on long term interest rate risk are complemented by the use of derivatives to take a larger position on interest rate movements. Conversely, a negative interaction variable and/or opposing coefficient signs (negative v. positive) between interest rate swap notional values and interest rate risk will indicate that banks are hedging positions in interest rate risk using their swap positions to mitigate losses in interest based income. In addition to swaps, interest rate forward and future notional values are included in the call report dataset.

- *Interest Rate Swap Mark to Market Values* These valuations of the market value of IR derivative positions are required to be updated quarterly for trading derivatives. Unlike the notional values which give the size of the position, mark-to-market values give the aggregate value of the bank's swap positions on the open market, provides insight on the swap markets' perception on the banks' positions as opposed to simply just the size. Additionally, trading revenues and losses from these derivatives are also included. However, these are retroactive in nature and capture positions that the bank's traders have unwound over the quarter, reflecting values at any point in the quarter. These could be inconsistent with the banks' overall interest rate risk management policy and gap positions on its balance sheets. Previous literature on swap usage by

BHCs found that fair values of IR derivative positions do not increase equity values when controlling for IR derivative notional values (English, W., Van den Heuvel, S., Zakrajsek, E., 2012).

Variable	Mean	Standard Deviation	Correlation
Avg. NIMs	0.04	.002	1.00
Fed Funds Rate	0.02	0.02	0.29
US GDP	$13919.17B	2197.28	-0.84
BAML Credit Spread	0.02	0.01	-0.14
CPI	206.30	20.82	-0.80
LLR	0.02	0.01	0.12
Spread.Value	1.51	0.93	-0.03
T10.YR.Rate	0.04	0.01	0.61
KBW.Index	75.05	23.76	0.15
LOAN.COMM.Value	$1187034.83 B	221916.67	-0.82
SPX	1285.51	282.46	-0.60
LIBOR.1M.Rate	0.02	0.02	0.27
LIBOR.3M.Rate	0.02	0.02	0.24
LIBOR.6M.Rate	0.02	0.02	0.23
LIBOR.12M.Rate	0.03	0.02	0.26
SWP.LIBOR.1YR.Rate	0.02	0.02	0.29
SWP.LIBOR.5YR.Rate	0.03	0.02	0.50
SWP.LIBOR.10YR.Rate	0.04	0.01	0.59
LIBOR.1M.VOL	0.15	0.21	-0.10
LIBOR.3M.VOL	0.12	0.10	0.07
LIBOR.6M.VOL	0.15	0.12	0.22
LIBOR.12M.VOL	0.21	0.16	0.31
T5YR.VOL	0.42	0.23	-0.38
T10YR.VOL	0.28	0.13	-0.31
T30YR.VOL	0.20	0.09	-0.32

Table 4.1: Macroeconomic Variable Descriptive Statistics

Variable	Description
Avg. NIMs	Average Net Interest Margins for U.S. Commercial Banks
Fed Funds Rate	Quarterly Avg. of Federal Funds Rate
US GDP	Quarterly U.S. GDP
BAML Credit Spread	Proxy for credit risk
CPI	Consumer Price Index; indexed to 1984
Loan Loss Reserve	Ratio of LLR to Assets
Spread.Value	Proxy for Shape of Yield Curve
U.S. 10 yr. Rate	10 Yr. U.S. Treasury Rate
KBW Index	Index of bank stock prices
Commercial Loans	Aggregate of outstanding loans to corporates
SPX	S&P 500 equity index value
1 Month LIBOR	1 Month LIBOR borrowing Rate
3 Month LIBOR	3 Month LIBOR borrowing Rate
6 Month LIBOR	6 Month LIBOR borrowing Rate
12 Month LIBOR	12 Month LIBOR borrowing Rate
1 Year LIBOR Swap Rate	Pay fixed LIBOR Swap; 1 yr. contract
5 Year LIBOR Swap Rate	Pay fixed LIBOR Swap; 5 yr. contract
10 Year LIBOR Swap Rate	Pay fixed LIBOR Swap; 10 yr. contract
1 Month LIBOR Vol.	90 day volatility of 1 Month LIBOR
3 Month LIBOR Vol.	90 day volatility of 3 Month LIBOR
6 Month LIBOR Vol.	90 day volatility of 6 Month LIBOR
1 Month LIBOR Vol.	90 day volatility of 12 Month LIBOR
T5YR.VOL	90 day volatility of yields on 5 yr. U.S. Treasuries
T10YR.VOL	90 day volatility of yields on 10 yr. U.S. Treasuries
T30YR.VOL	90 day volatility of yields on 30 yr. U.S. Treasuries

Table 4.2: Macroeconomic Variable Descriptions

Variable	Mean	Standard Deviation	Corr. W/ NIMs
NIM	0.01	0.00	1.00
ST.MATURITY.GAP	0.52	0.23	0.14
LT.MATURITY.GAP	-.29	.75	.06
IR.DER.TRAD.FAIR	$103 B	$289 B	-0.19
IR.DER.NONTRAD	$115 B	$261 B	0.03
IR.DER.TRADE	$6.2 T	$15 T	-0.21
IR.FUT	$218 B	$503 B	-0.20
IR.FWD	$712 B	$1.9 T	-0.17
tier1.leverage	7.63	2.17	0.24
total.capital	$36 B	$52 B	-0.08
TIER2.CAPITAL	$9.5 B	$13 B	-0.05
prov.loanlease	$718 M	$1.6 B	0.03
risk.weighted.assets	$279 B	$384 B	-0.06
Net.IR.Risk	1.38	3.59	0.14
net.int.income	$2.6 B	$3.7 B	0.05

M = Million, B = Billion, T = Trillion

Table 4.3: Panel Data Summary Statistics; 18 Banks

Variable	Description
NIM	Net Interest Margins
ST.MATURITY.GAP	GAP for assets/liabilities repricing w/in 1 year
LT.MATURITY.GAP	GAP for assets/liabilities repricing greater than 1 year
IR.DER.TRAD.FAIR	Gross Fair Value of Interest Rate Derivatives held for trading
IR.DER.NONTRAD	Notional value of IR derivative contracts for non-trading purposes
IR.DER.TRADE	Notional value of IR derivative contracts for trading purposes
IR.FUT	Notional Value of IR futures contracts
IR.FWD	Notional Value of IR forwards contracts
tier1.leverage	Ratio of tier 1 capital to total assets
TIER2.CAPITAL	Value of Tier 2 Capital
total.capital	Includes measures of tier 1, tier 2, and tier 3 capital
prov.loanlease	Capital set aside for allowance of bad loans
risk.weighted.assets	Measure of total assets weighted by credit risk
Net.IR.Risk	Ratio of net interest income to total income
net.int.income	Interest income subtracted by interest expenses

Table 4.4: Panel Data Statistics Despcriptions

5 Empirical Methodology

5.1 Introduction

As mentioned in previous sections, the goal of this paper is to build econometric models that explain, with significance and without bias, the variation in NIMs for U.S. commercial banks. Presented in this section are data transformations and the specifications, assumptions, and methodology for the two models.

5.2 Data Transformation

5.2.1 Stationary Time Series

In order to perform different time series and panel data regressions without, the dependent variable (NIMs) must be transformed to a stationary time series (Stock & Watson, 2007). A stationary time series is a time series with a deterministic linear trend across the period as opposed to a stochastic time series in which current values in a time series depend both on its previous value and the variance at the previous period (Stock & Watson, 2007). Stochastic regressors and dependent variables cause bias in autoregressive coefficients and lead to non-normally distributed t-statistics for regression coefficients (Stock & Watson, 2007). Conversely, a stationary time series has constant variance and a constant mean, or a mean that changes according to a defined linear trend across time (Stock & Watons, 2007). The intuition behind this transformation is to remove movements in variance over time to prepare variables for ordinary least squares methods. This is achieved by performing Dickey-Fuller tests on time series to identify stochastic trends, apply transformations to the data, such as lags or first differencing, and reapply the Dickey-Fuller test for stochasitic trends to confirm that the data is now stationary.

5.2.2 Principal Component Analysis

Principal Component Analysis (PCA), as used in multivariate regression methods, employs linear transformations over a (nxp) decision matrix of data to remove multicolineraity from a set of p variables with high correlation by transforming the variables to a smaller number of variables called principal components (Richardson, 2009).(footnote or include full explanation). The process applies linear algebra to create a matrix consisting of principal components by calculating a new basis matrix consisting of orthogonal, and therefore uncorrelated, vectors each maximizing total variance from the original vector (Richardson, 2009). The dimensionality of the data can also be reduced, because most of the total variance in the correlated data can be explained by the first few principal components; consequently, a regression model will require fewer explanatory variables to capture the total variance. Principal Component Analysis has been employed by economists and banks alike to account for variation in interest rates and rate volatility and remove correlation between explanatory variables. This paper explores Principal Component Analysis on short term LIBOR rates, LIBOR swap prices, 90 day rolling volatility of LIBOR rates, and 90 day rolling volatility for US Treasury rates.

5.2.3 LIBOR Rates

LIBOR rates represent some of the most important variables in the empirical models, as LIBOR movements affect cash flows on many short term assets, and therefore affects short term repricing risk and earnings from short term risk exposure. An effective model of the variation in the term structure of LIBOR rates will be essential in the empirical methodology. Table 5.1 gives a correlation matrix of LIBOR rates across the length of the dataset, and indicates a significant level of correlation across rates over time. Figure 5.1 shows the variance for each principal component over the time series. Consistent with uses of PCA in multivariate regression analysis, we include the principal components that explain the most variance in the data which is indicated by the relative variance of each PC. The proportion of total variance explained by the inclusion of the first PC value is 99.5% indicating that only the first PC needs to be included in regression models to capture a significant amount of the variance.

	1 Month LIBOR Rate	3 Month	6 Month	12 Month
1 Month	1.00	1.00	0.99	0.99
3 Month	1.00	1.00	1.00	0.99
6 Month	0.99	1.00	1.00	1.00
12 Month	0.99	0.99	1.00	1.00

Table 5.1: LIBOR Rate Correlation Matrix

5.2.4 LIBOR Swap Prices

Additionally, correlation is identified across the interest rate swap prices for pay-fixed receive-floating swaps for LIBOR Rates with contract maturities of 1, 5,

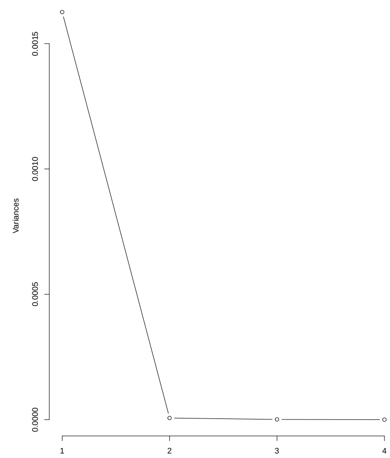

Figure 5.1: LIBOR Rate PC Variance

and 10 years respectively. Table 5.2 gives the correlation of LIBOR swap prices for the period. Similarly to the LIBOR interest rate values, there is a high degree of correlation that demands PCA transformation. Additionally, the variance for each PC value is given in Figure 5.2 which indicates that the vast majority of variance in LIBOR rates is captured by the first PC value.

	1 Year LIBOR Swap Rate	5 Year Rate	10 Year Rate
1 Year Rate	1.00	0.93	0.87
5 Year Rate	0.93	1.00	0.99
10 Year Rate	0.87	0.99	1.00

Table 5.2: LIBOR SWAP Rate Correlation Matrix

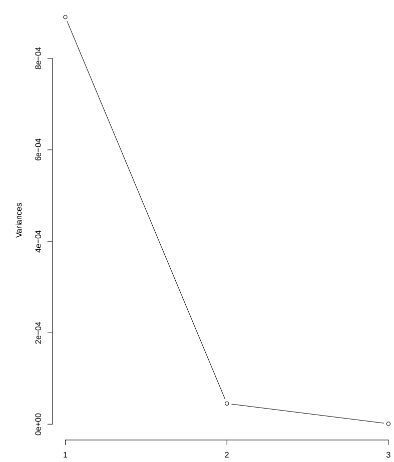

Figure 5.2: LIBOR Swaps PC Variance

5.2.5 LIBOR Volatility

A significant amount of multicolinearity is also identified in interest rate volatility, both for the short term LIBOR rates and the medium to long term U.S. Treasury rates. Interest rate volatility is an integral part of theory behind net interest margins and will play an important role in the paper's empirical models. The correlation matrix for LIBOR 90 day volatility is given in Table 5.3. The plot of PC variance for 90 day LIBOR volatility is given in Figure 5.3. In a slight contrast to the other PCA transformed variables, the variance in LIBOR volatility is explained by the first two principal components. Accordingly, the first two PCs for LIBOR vol. will be included in the analysis.

	Vol. 1 Month	Vol. 3 Month	Vol. 6 Month	Vol. 12 Month
Vol. 1 Month	1.00	0.87	0.70	0.48
Vol. 3 Month	0.87	1.00	0.91	0.70
Vol. 6 Month	0.70	0.91	1.00	0.92
Vol. 12 Month	0.48	0.70	0.92	1.00

Table 5.3: 90 Day Vol. LIBOR Rates Correlation Matrix

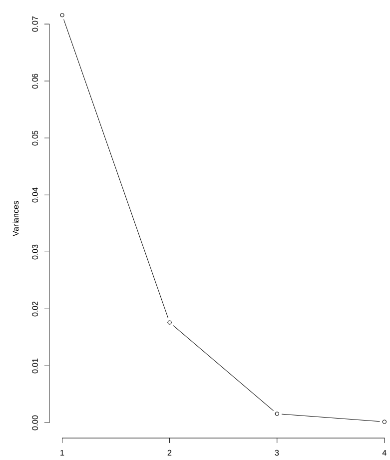

Figure 5.3: LIBOR Volatility PC Variance

5.2.6 US Treasury Rate Volatility

The correlation matrix of 90 day U.S. Treasury rates is given in Table 5.4 and indicates high degrees of correlation across the period of the dataset. Furthermore, the variance of the principal components indicate that first PC describes the vast amount of variance of U.S. Treasury rates over the dataset and will be used in subsequent models.

	Vol. 5 yr.	Vol. 10 yr.	Vol. 30 yr.
Vol. 5 yr.	1.00	0.97	0.90
Vol. 10 yr.	0.97	1.00	0.96
Vol. 30 yr.	0.90	0.96	1.00

Table 5.4: 90 day U.S. Treasury Rate Volatility Correlation Matrix

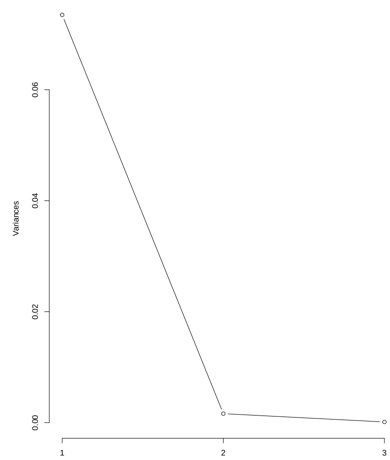

Figure 5.4: U.S. Treasury Volatility PC Variance

5.2.7 Additional Transformations

In addition to corrections for multicolinearity and non-stationary time series data, a few supplementary transformations are made to the data to account for outliers, skewness, and large values for a number of different variables.

log(LOAN.COMM)	log(SPX)
log(GDP)	log(1 + total.capital)
log(1 + IR.DER.TRADE.FAIR)	log(1 + IR.DER.NONTRADE)
log(1 + IR.FUT)	log(1 + risk.weighted.assets)
log(1 + IR.DER.TRADE)	log(prov.loanlease)

Table 5.5: Variables with Log Transformation

5.3 Macro Model (Model 1)

The first model fitted uses the aggregate NIMs value for all U.S. commercial banks as the dependent variable. The focus on macro data variables help frame the larger, integrated model later on and also provide intuition on how bank NIMs perform on average over the period. Moreover, this macro model is analogous to the "pure spread" models proposed by Ho & Saunders (1981) and Saunders & Schumacher (2000) as it predicts an average value for the market. Model 1 fits an auto regressive intergrated model on NIMs between periods. The first difference component is necessary to construct a stationary time series (see section 5.1.1). The formula for an autoregressive series model with p autoregressive lags and q explanatory variable lags is given in equation 5.1, and the assumptions for a best linear unbiased estimator model are presented below. Analysis of Dickey-Fuller tests determines the optimal lag count for the dependent variable ($p = 1$) while the first difference transformation is adequate for making the macro dataset stationary.

$$
\begin{aligned}
Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p}, \\
+ \delta_{11} X_{1t-1} + \delta_{12} X_{1t-2} + \ldots + \delta_{1q_1} X_{1t-q_1}, \\
+ \ldots + \delta_{k1} X_{kt-1} + \delta_{k2} X_{kt-2} + \ldots + \delta_{kq_k} X_{kt-q_k} + \mu_t
\end{aligned} \tag{5.1}
$$

5.3.1 Assumptions for Time Series Regression w/ Multiple Predictors

- $E(u_t | Y_{t-1}, Y_{t-2}, \ldots, X_{1t-1}, X_{1t-1})$
- a) The random variables $(Y_t, X_{1t}, \ldots, X_{kt}$ have stationary distribution, and b) $(Y_t, X_{1t}, \ldots, X_{kt})$ and $(Y_{i-j}, X_{1t-j}, \ldots, X_{kt-j})$ become independent as j gets large;
- Large outliers are unlikely; X_{1t}, …, X_{kt} and Y_t have nonzero, finite fourth moments.
- There is no perfect multicolinearity

5.3.2 Alkaine Information Criterion

However, unlike more common linear regression methods, R values are not calculated for autoregressive time series models. Rather, models are compared based on their Alkaine Information Criterion (AIC). The equation for AIC is given in equation 5.2 where k is the number of model parameters, and L represents the maximum value of the model's likelihood function. An optimal model will minimize the AIC value across other fitted models, but it does not provide an absolute measure of accuracy, which is a limitation in interpreting the results of the models. Also, note that a larger number of parameters (explanatory variables) included will penalize the model. Lastly, there are Bayesian adjustments to the AIC (BIC) that improve model selection quality in certain scenarios (Stock & Watson, 20007).

$$AIC = 2k - 2ln(L) \tag{5.2}$$

5.4 Panel Model (Model 2)

The second model explored is a first difference (FD) panel data regression for NIMs. The FD model is an extension of the fixed effect panel regression model (equation 5.3), a model that aims to control for omitted variables that are time-invariant, but vary across observations. The first difference transformation makes the response variables (NIMs for each bank) stationary which allows for regression analysis on the data and removes high autocorrelation that was present in preliminary basic fixed effects models. Additionally, a autoregressive explanatory lag is also included in the FD model, meaning that changes in NIMs from quarter to quarter are dependent on changes between the previous two quarters. However, the time invariant fixed effect (δ_i) is subtracted out of the regression model, which does not allow us to analyze the fixed effects on NIMs of each specific BHC. Furthermore, the FD model sees a significant reduction in R^2 from the FE model. However, this tradeoff in predictive power is necessary to remove bias across time in the model.

$$y_{i,t} = \delta_i + \beta X_{i,t} + \mu_{i,t} \tag{5.3}$$

$$\Delta y_{i,t} = y_{i,t} - y_{i,t-1} = \beta \Delta X_{i,t} + \Delta \mu_{i,t} \tag{5.4}$$

5.4.1 Assumptions

The assumptions for first difference estimation are the same as the fixed effects regression model, but for first differenced data as opposed to the raw data (Stock, & Watson, 2007).

- $\Delta u_{i,t}$ has conditional mean zero: $E(\Delta u_{i,t} — \Delta X_{i,1}, \ldots, \Delta X_{i,T}) = 0$.
- $(\Delta X_{i,1}, \Delta X_{i,2}, \ldots, \Delta X_{i,T}, \Delta u_{1,t}, \Delta u_{2,t}, \ldots, \Delta u_{i,T})$ are i.i.d. draws from their joint distribution
- Large outliers are unlikely; $(\Delta X_{i,t}, \Delta u_{i,t})$ have nonzero finite fourth moments.
- There is no perfect multicolinearity.

6 Results

6.1 Macroeconomic Model (Model 1) Results

Model 1 gives provides a good framework of the effects of macroeconomic variables over the period 2000-2014. The model uses using 60 total observations and 16 explanatory variables, including the autoregressive term and the selected principal components (see section 5.1) to forecast the first difference in NIMs. Additionally, Model 1's residuals indicate normally distributed error terms centered around 0 across the time of the dataset as shown in figures 6.2 and 6.3. However, there is a slight upward bias in the model towards the end of the time series, as shown in Weakly supporting the normal, uncorrelated distribution of the error terms is the model's Dickey-Fuller test, which rejects the null hypothesis at the 10% significance level. The autocorrelations of the residuals are also shown in figure 6.1.

When interpreting the coefficients of the model, it is useful to refer to the distribution of the corresponding variable (see table 4.1) to understand typical variation of the variable over time. Many variables included in the model vary little over the time period, and this is reflected in the small standard deviations. The largest coefficient in Model 1 is for the loan loss reserve to total asset ratio which has a coefficient of .25 and is significant at the 5% level. A one standard deviation increase in aggregate LLR from the mean (2%) would increase, on average, the difference between contiguous period NIMs by .5% which is a large increase on NIMs given then mean value is around 4%. Model 1 suggests that increasing the total loan loss reserves

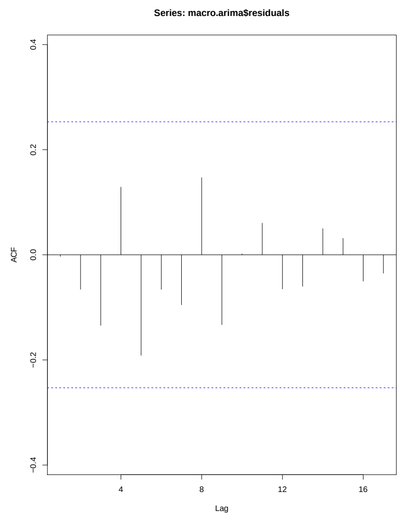

Figure 6.1: Model 1 Residual Autocorrelation

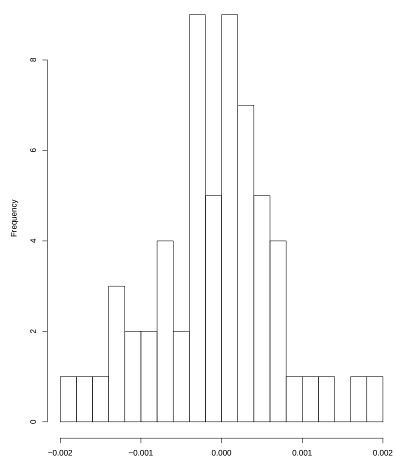

Figure 6.2: Model 1 Histogram of Residuals

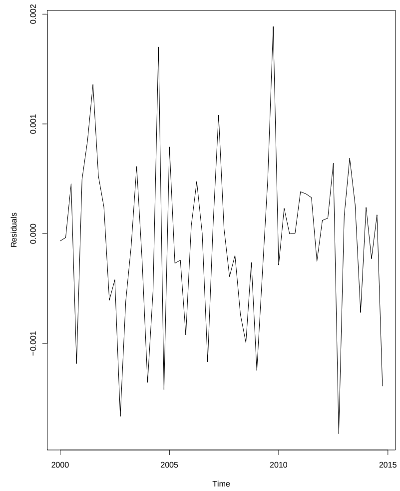

Figure 6.3: Model 1 Residuals over Time

to asset ratio in the banking system is beneficial for bank profitability as banks are able to pass the cost of holding capital to creditors. This also suggests that credit risk aversion, and perhaps more importantly banks' choices to plan for credit risk by setting aside capital, supports healthy margins.

The Federal Funds coefficient, although not significant, indicates that changes in the Fed Funds rate, in our model also have large positive effect on NIMs, relative to other variables in the model. A theoretical one standard deviation increase (2%) in the Federal Funds rate would increase the difference in NIMs across the period by .12%, which is a substantial uptick on the margins.

Interestingly, the spread value between 10 year and 2 year US treasuries has a negative effect on NIMs has a small, negative effect on the aggregate net interest margin value. This conflicts with theory on maturity transformation that posits that a steeper yield curve supports stronger bank earnings. Next, inflation (CPI index) is significantly negatively associated with a coefficient of -.0002. It is important to note that CPI, unlike the rate variables has a large standard deviation (20.04), and a one standard deviation in the CPI index would lower differences in NIMs across periods by .4%, a significant amount. This association could simply be due to increasing inflation overtime while NIMs have decreased in recent years. log(GDP) is significantly positively associated with NIMs, conflicting with theory that postulates that NIMs are countercyclical.

Analyzing the coefficients for PCs can be a bit confusing, but with the proper understanding of the underlying theory, the significance of the variables in the regression can be interpreted. The next significant explanatory variable worth discussing first PC for LIBOR rates. The first PC for LIBOR rates, which explains upwards of 99% of the variation in LIBOR rates across the dataset has a positive, but non-significant, association with NIMs, indicating that increases in LIBOR short term rates are beneficial for U.S. commercial banks. Supporting this is the positive coefficient for U.S. 10 yr. treasury yields. However, when we turn to volatility effects on NIMs, we see a small positive association with LIBOR volatility (via the first PC, which explains around 80% of the variation in total LIBOR volatility). Note the second LIBOR PC variable has a negative association with NIMs; this is expected, as the methodology of PCA defines orthogonal (opposite directed) vectors to reduce multicolinearity. Furthermore, the second PC for LIBOR vol. explains merely 14% of variation in LIBOR vol. Therefore, the model suggests that increases in short term IR volatility is good for bank NIMs. Conversely, volatility in US treasuries, seen in the first PC (which explains 98% of the variation in medium and long term U.S. treasury volatility) has a significantly negative effect. Compare this with findings from Ho and Sauders who find that long term volatility in interest rates affects the "pure spread" earned by banks as financial intermediaries while short term rates had no significance (Ho and Saunders, 1981).

Model 1 is a good introduction of the effects of the macro variables, but the effects demonstrated by the model do not adequately control for other variables correlated with NIMs. Additionally, there are a number of non-significant variables in the model as well which were kept to decrease the model's AIC. However, with the integration of bank specific variables, the paper will be able to further isolate the effects of the macro variables discussed here.

6.2 Panel Regression (Model 2) Results

The results of the first difference panel regression model in some ways conflict with the results of the autoregressive macro model, but also support some of the results. When comparing results from the two models, it is useful to keep in mind that the panel model controls for micro, firm level data and predicts firm level NIMs while the macro model uses only macro data and predicts the average level of NIMs for *all* insured U.S. commercial banks. Therefore, a decent amount of variation between the two models is understandable. Moreover, the predictions in the panel model are not for the actual NIMs spread rather the net interest earnings weighted by average total consolidated assets. The panel model offers interesting results to be compared with previous literature and theory on financial intermediation and IRR. The final model is taken from an unbalanced panel-[1], includes 27 explanatory variables and a total of 872 observations from the dataset, as some observations were dropped that did not contain complete information on the particular BHC. The final model has an R^2 value of .199, indicating some, but not a lot, of explanatory power for the model and that a lot of the variation in differences are attributed to the random error terms. The preliminary FE model had a significantly larger R^2,

[1] Individual BHCs do not contain all 60 observations across time

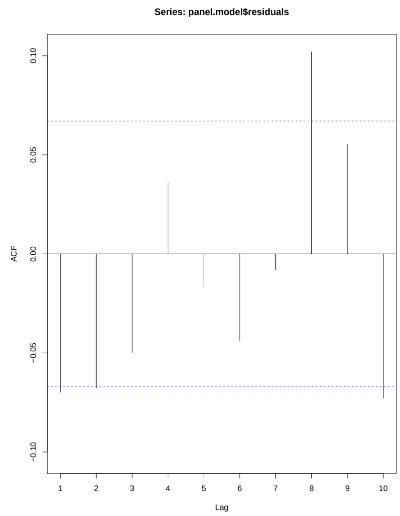

Figure 6.4: Model 2 Residual Autocorrelation

suggesting that the effects of time invariant variables, or those that change by small amounts over time, are effective in predicting NIMs. Finally, there is almost no autocorrelation of residuals, and the residuals are normally distributed around 0 for the duration of the model, shown in figures 6.4 and 6.5.

Regression coefficients may seem tricky to interpret for first difference regression models because the model regresses *changes on changes*. However, the interpretation of the coefficients are the same as for a fixed effects regression model, what changes in the methodology for computing the coefficients. (Woolbridge, 2010). Therefore, the coefficients represent the change in NIMs with a one unit increase in the corresponding explanatory variable. The intercept measurement, in theory, gives the linear trend of the differences in NIMs over time, controlling for other variables. In our model, the intercept value is not significant and has a positive value. However, the downward trend in NIMs is captured by the lag of differences variable, which is highly significant, with a coefficient of -.2873. Therefore, larger differences in NIMs

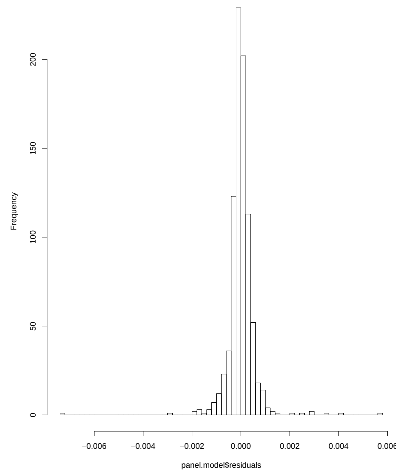

Figure 6.5: Model 2 Histogram of Residuals

indicate that NIMs will be smaller in subsequent periods. The lagged dependent variable added a significant amount of predictive power to the model, improving the R^2 by .1.

The kpanel model identified a large number of significant explanatory variables a one unit increase in the tier 1 leverage ratio (ratio of tier 1 capital to assets) has a negative effect of 6.3E-5 (.000063) on NIMs. At face value, this is consistent with theory that postulates higher capital ratios lower bank profitability as an opportunity cost of not lending. However, the log of total capital is significant with a positive coefficient suggesting that increasing total capital is beneficial for NIMs. A 1% change in the total capital held on the BHC's balance sheet roughly equates to an increase in NIMs of .0000013. The model could suggest that increasing initial, core capital could lower BHC earnings, but at a point, additional capital is beneficial to earnings, and banks are able to pass along the costs of holding additional capital but not the costs of core capital. Additionally, the differences in coefficients could also be attributed to the fact that the tier 1 leverage is a ratio while the total capital measurement is not, which could embed the effect of size of the institution. However, similar coefficients were obtained when total capital was weighted by total assets, but the coefficients for both ratios were no longer significant.

One of the most significant variables in the model was risk weighted assets. The coefficient for log(1 + rwas) is negative indicating that a 1% increases in RWAs lowers NIMs by 1.2E-5 (.000012) which is about .6% of the standard deviation of NIMs for the period. This tells us that larger and more risky holdings decrease NIMs, controlling for other factors. However, as mentioned previously, the RWA value fails to distinguish between effects of size and risk.

The spread between 10 and 2 year treasury rates is also extremely significant in the model. Consistent with "conventional wisdom" behind maturity transformation theory and previous studies, increases in the slope of the yield curve (steepening of the yield curve) are positive for bank NIMs. Increasing the spread, or steepening the yield curve, by 1 standard deviation (.009) marginally increases NIMs by .00027 or a by 2.8% for the mean NIMs value in the panel dataset. The panel model finds evidence of a positive effect of the yield curve, but this conflicts with the slightly negative coefficient for spread in the macro model, suggesting that controlling for firm-level factors leads to a positive effect on individual bank NIMs.

The short term GAP value was not significant, but the long term GAP value was positively significant at the 5% level, indicating that NIMs increase by .0011 for a one unit increase in the long term maturity GAP ratio. The mean LT GAP is -.29, meaning that BHCs maintain negative exposure to long term rates, on average. As banks approach positive exposure for long term rates, NIMs increase. This is consistent with what was predicted, as banks earn more on longer term exposures. The also model identified a few significant interaction terms between LT GAPs and interest rate variables. The negative interaction terms between LT GAP and the 10 year U.S. treasuries, indicates that the gains from long term exposure are lessened as rates rise. This is consistent with findings from Angbazo (1997) that banks with higher IRR profiles are hurt more during rate increases. Additionally, volatility in U.S. treasury rates also decreases the positive effects of LT rate exposure, suggesting that volatility in rates may not be beneficial for banks with heavy LT interest rate exposure.

Continuing with rate volatility, all PCs for interest rate volatility (U.S. treasuries and LIBOR rates) are negatively significant in the panel model, contesting previous findings that rate volatility is helpful for bank earnings (Ho & Saunders; Saunders Schumacher). Since the macro model is similar to the dealership model, one explanation for this discrepancy could be the difference between the "dealership model", in which the pure spread increases linearly with IR volatility, and firm level models that look at how firms deviate from the pure spread. Looking back at the macro model, we see that LIBOR volatility is marginally positively associated with average NIMs, but U.S. treasury volatility is negatively associated with NIMs. The negative effect of U.S. remains when controlling for micro factors, while LIBOR volatility coefficient switches from positive to negative. This could be a result of controlling for individual bank interest rate risk exposure.

In addition to negative coefficients for IR volatility, the panel model also finds that the PC for LIBOR rates is negatively associated with NIMs and the 10 year U.S. treasury rate is negatively associated with NIMs at the micro level. The Federal Funds rate was not significant and therefore dropped from the model. This is consistent with findings that rate increases have an adverse effect on equity values of banks and bank earnings (Flannery, & James, 1984; Angbazo, 1997).

Another interesting contrast with the macro model is the change of coefficient signs for both the log of the S&P 500 and the log of GDP value. In the macro model, these coefficients are negative and positive respectively. However, in the panel model, the coefficient for the log of the S&P 500 is positive, and the coefficient for log of GDP is negative. This implies, when controlling for micro level variables, higher individual NIMs are associated with higher U.S. equity values and lower GDP. This corresponds with past findings that suggest NIMs are counter cyclical, and NIMs are correlated with higher overall stock performance (Alliaga-Diaz, & Olivero, 2011).

Lastly, the panel model finds only one interest rate derivative value with a significant effect on NIMs. The panel model suggests that interest rate futures have a significantly positive effect on NIMs, albeit very small (3.7E-5). There is no consistent evidence to support the claim that interest rate derivatives have any effect on NIMs. Other variables that were not significant include the BAML credit spread, inflation rates, and total value of outstanding corporate loans.

	Coefficient	Standard Error	P-Value
ar1	0.06	0.17	0.72
FF.Rate	0.06	0.07	0.35
BAML.Rate	0.02	0.05	0.65
CPI.Value	-2E-4	0.00	0.02**
LLR.Rate	0.25	0.11	0.02**
Spread.Value	-.04	0.07	0.61
T10.YR.Rate	0.07	0.06	0.20
LIBOR.Rate.PCA1	0.02	0.04	0.59
SWP.PCA1	0.03	0.02	0.19
UST.PCA1	-2E-3	0.00	0.04**
LIBOR.VOL.PCA1	3E-4	0.00	0.69
LIBOR.VOL.PCA2	-1E3	0.00	0.31
log.LOAN.COMM	-3E-3	0.01	0.64
log.SPX	-3E-4	0.00	0.74
log.GDP	0.02	0.01	0.02**
log.KBW	-3E-3	0.00	0.05*
AIC	-644.43		
AICc	-629.51		
BIC	-609.12		
Log Likelihood	339.22		
Note:	*p<0.1;	**p<0.05;	***p<0.01

Table 6.1: Results from Model 1

	Estimate	Std. Error	t-value	Pr(>|t|)
(intercept)	0.0000	0.0000	0.19	0.8471
lag(NIM, 1)	-0.2873	0.0275	-10.43	0.0000***
ST.MATURITY.GAP	-0.0002	0.0002	-0.94	0.3469
LT.MATURITY.GAP	0.0009	0.0005	1.73	0.0842*
log(1 + IR.DER.TRAD.FAIR)	-0.00006	0.0000	-1.44	0.1501
log(1 + IR.DER.NONTRAD)	0.00002	0.0000	0.63	0.5259
log(1 + IR.DER.TRADE)	0.0000	0.0000	1.02	0.3077
log(1 + IR.FUT)	0.00003	0.00004	3.07	0.0022***
log(1 + Merger.Value)	-7E-6	0.0000	-1.81	0.0706*
log(1 + risk.weighted.assets)	-0.0012	0.0002	-7.47	0.0000***
tier1.leverage	-0.0001	0.00006	-1.89	0.0586*
Spread.Value	0.03	0.01	2.51	0.0121**
log(1 + total.capital)	0.0014	0.0002	7.47	0.0000***
log(1 + prov.loanlease)	0.00002	0.0000	1.35	0.1774
LLR.Rate	0.0279	0.0182	1.54	0.1245
Note:	*p<0.1;	**p<0.05;	***p<0.01	

Table 6.2: Results from Model 2 (Part 1

	Estimate	Std. Error	t-value	Pr(>|t|)
UST.PCA1	-0.0003	0.0002	-1.69	0.0908*
T10.YR.Rate	-0.0364	0.0089	-4.09	0.0000***
SWP.PCA1	0.0123	0.0040	3.07	0.0022***
LIBOR.Rate.PCA1	-0.0203	0.0063	-3.20	0.0014***
LIBOR.VOL.PCA1	-0.0004	0.0002	-2.78	0.0056***
LIBOR.VOL.PCA2	-0.0004	0.0002	-1.70	0.0896*
log.LOAN.COMM	-0.0005	0.0008	-0.57	0.5689
log.SPX	0.0010	0.0004	2.73	0.0065***
log.GDP	-0.0071	0.0033	-2.15	0.0315**
ST.GAP:LIBOR.Rate.PCA1	-0.0070	0.0071	-1.00	0.3192
LT.GAP:T10.YR.Rate	-0.0308	0.0120	-2.57	0.0104**
LT.GAP:UST.PCA1	-0.0003	0.0002	-1.68	0.0929*
LT.GAP:Spread.Value	0.0001	0.0001	0.62	0.5340
Observations	854			
R^2	0.206			
Adjusted R^2	0.199			
F Statistic	7.926***	(df = 27; 826)		
Note:	*p<0.1;	**p<0.05;	***p<0.01	

Table 6.3: Results from Model 2 (Part 2)

7 Conclusion

This paper analyzes the effects of macro economic conditions, interest rate risk, and bank positions on U.S. bank holding companies' net interest margins. Previous literature establishes links between interest rate risk, such as maturity GAPs, and NIMs. This paper presents two different regression models that attempt to isolate and quantify the determinants of bank net interest margins on a quarterly basis across the period 2000 - 2014. The first model uses a selection of macroeconomic variables to build an autoregressive model for the average net interest margins for all U.S. commercial banks. Some of the model's results complement previous literature, such as the association of short term LIBOR volatility and loan loss reserves with higher NIMs. However, many of the macro model's results are inconclusive or inconsistent with previous literature, suggesting that the effects of some macroeconomic variables cannot be isolated without controlling for firm level variables. The second model expands on the macro model's methodology and fits a first difference panel regression model on a sample of 18 different U.S. BHCs from the same period. The integration of macro elements and bank specific positions leads to a more complete model. The model establishes a logical link between the long term maturity gap and margins. The panel model confirms the "conventional wisdom" of a steeper yield curve supporting bank margins and the theory that the costs of holding higher capital reserves are efficiently passed along to consumers in the form of higher loan rates and therefore positively associated with NIMs. Furthermore, it suggests that raises in interest rates hurt bank margins, controlling for other variables. Finally, the model finds one significant link between interest rate derivatives and margins: interest rate futures are beneficial for margins. The model found no significant interaction between IR derivatives and GAP profiles, lending no insight on whether banks are hedging or taking on active IRR exposure with derivatives. The models presented do a good job framing influences on banking margins, but there is definitely room for improvement in further research, such as including values for banking market structure and product specialization for each bank. In conclusion, this study suggests links between values of interest rate risk exposure, term structures, and capital levels and bank margins that can provide insight for bank management policies and bank regulation policies alike.

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