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Master's Degree in Corporate Finance

The effects of a change in interest rates on the reclassification of securities: An empirical analysis.

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Nomenclature

ABS Asset Backed Securities

AFS Available for Sale

AOCI Accumulated other comprehensive income

CAR Capital Adequacy Ratio

CCAR Comprehensive Capital Analysis and Review

CET1 Common Equity Tier 1

CMBS Commercial Mortgage Backed Securities

COGS Cost of Good Sold

FAS Financial Accounting Standards

FASB Financial Accounting Standards Board

FHLMC Freddie Mac

FIFO First in First Out

FNMA Finnie Mae

GAAP Generally Accepted Accounting Standards

GNMA Ginnie Mae

HFT Held for Trading

HTM Held to Maturity

LCR Liquidity Coverage Ratio

LIFO Last in First Out

NSFR Net Stable Funding Ratio

RMBS Residential Mortgage Backed Securities

RWA Risk Weighed Assets

SLR Supplementary Leverage Ratio, Total Leverage ratio

SLR Supplementary Leverage ratio

UMBS Uniform Mortgage Backed Securities

Abstract

The goal of my analysis here was to study what brings bank to reclassify securities from AFS to HTM and the impact that this choice has had on the volatility of the regulatory capital of banks and on the liquidity of markets. In chapter three we see that during periods of market calmness changes in Interest rates are the main driver of the choice of banks to reclassify. However during period of market stress, while still remaining relevant, they are not the only factor that comes into play; Leverage seems to play an important role too and this is understandable as more leveraged banks may have difficulties in managing losses on their securities portfolios. I then dove deeper and I found that Bank of America, JP Morgan, Citi and Morgan Stanley were the banks that were affected the most by Leverage during periods of economic downturn and as a result, as I was expecting, I received confirmation that these four banks reclassified throughout the whole crisis period more than the other banks did, thus allowing them to be far less exposed to losses in their portfolio than the other seven banks in the data sample size. In terms of types of securities that have been reclassified from AFS to HTM, RMBS seemed to be the preferred asset class, and more in detail Finnie Mae and Freddie Mac RMBS were reclassified more under HTM than AFS than Ginnie Mae RMBS: differences in government backing make Finnie Mae and Freddie Mac a stronger candidate for reclassification than Ginnie Mae.

A lower volatility of regulatory capital was another benefit these four banks were able to achieve as a result of the higher HTM reclassification. This is a crucial aspect we want to consider as the regulators, but also the market and the investors closely monitor this parameter, especially when the bank is known to have a higher than average Leverage exposure. Therefore this lower volatility combined with a higher capital adequacy ratio made these banks appear as healthier and more stable than they really were. Out of curiosity I then dug deeper to see how much of this reduction in volatility was really caused by the HTM reclassification and I found that, although significant, this was not the only factor involved. Banks appeared to have combined operations of higher HTM reclassification together with deleveraging part of their loan exposures, by mainly divesting the riskier residential mortgages.

At last, in term of liquidity, the higher HTM reclassification caused the liquidity of RMBS market to decrease, specifically regarding the Finnie-Mae and Freddie-Mac segments, as we know that once reclassified the securities cannot be sold as freely as they would be under AFS or HFT, unless the tainting of the entire portfolio which would cause an instant repricing of all the securities contained in that portfolio, causing the unrealized gain and losses to flow directly into the regulatory capital. As far as the data I gathered concern, Bank of America, JP Morgan, Citi and Morgan Stanley all together reclassified to HTM from 2% of their total assets in 2018 to almost

10% at the end of 2022, thus taking away from markets roughly $5bn of liquidity in 2018 to almost $35bn at the end of 2022. Among the various indices I calculated to prove the reduction in market liquidity, in my opinion the most significant of them all was the interdealer trades as it indicates that not only banks reclassified to HTM thus lowering the liquidity in the markets, but they also refused to absorb in their balance sheet the customer order imbalances by engaging in interdealer trades thus spreading these imbalances across the other dealers in the system, indicating that dealers were less willing to bear the full risk and potential costs associated with absorbing order imbalances. As last thought, I then followed logically and verified that if banks are remunerated to provide market with liquidity, then if the market is far less liquid then it used to be, the trading revenues for Bank of America, Citi, JP Morgan and Morgan Stanley should decrease accordingly, as the trading revenues can be seen as the compensation for banks for providing markets with liquidity.

Chapter 1

Accounting Background

1.1 HFT vs AFS vs HTM

When looking at a balance sheet of whichever entity it might be, it can be tempting to look at every entry as if the values reported were the only possible and acceptable solution. However this is hardly the case: the figures we see are just one way to look at the company under scrutiny. Let's think for instance at physical assets. Choosing one among normal, accelerated or declining balance depreciation methods significantly change the accounting value of the asset reported. A company using normal depreciation would show a higher value of assets and a higher net income in the first years compared to a firm using accelerated depreciation, thus appearing more profitable and solid. Or let's think about inventories. Under US GAAP (which allows for LIFO), in a period of increasing prices a company would show a higher valuation of its inventories under FIFO than under LIFO but a higher COGS under LIFO than under FIFO. These examples demonstrate how important it is for analysts to understand the accounting methods used by firms. When analyzing financial statements an analyst should not limit its focus on the numbers actually written in the reports, but he must critically think on a two-dimension basis: what is reported vs the accounting criteria used and its impact on the representation of the company.

When dealing with financial assets FAS 115 requires firms to classify each security upon acquisition into one of three categories: Held for Trading (HFT), Available for Sale (AFS), or Held to Maturity (HTM), based on their intent and ability to hold the security.

The HTM classification is designated for securities that the enterprise has the positive intent and ability to hold to maturity (FASB 1993). This positive intent and ability to hold to maturity is a binding commitment by the bank; HTM securities are prohibited from being sold or reclassified in response to liquidity needs or changes in market interest rates. Furthermore, any sale or reclassification of HTM securities risks "tainting" the entire HTM portfolio and losing the option to use the HTM classification for two years under SEC guidance. The appeal of the classification is that HTM securities are carried at amortized cost rather than being marked to market. This stabilizes key regulatory ratios, such as the supplementary leverage ratio (SLR), and therefore improves banks' performances on Comprehensive Capital Analysis and Review CCAR tests[1]. HTM is effectively a regulatory hedge for fixed income securities. However it must be noted that not all assets are eligible to be classified as HTM. For instance common stock and preferred stock are not classifiable as held-to-maturity securities, since they have no maturity dates, and so cannot be held to maturity. The same holds for derivatives and trade-able loans. In a nutshell, therefore, HTM classification mainly concerns fixed income instruments and more in particular: government bond and notes, corporate bonds, municipal bonds, asset backed securities and mortgage backed securities.

HFT securities are defined as securities that are bought and held principally for the purpose of selling them in the near term (FASB 1993). Securities classified as trading assets may be sold whenever it best suits the bank, but any fair value fluctuations contribute directly to regulatory capital volatility.

The catchall category is AFS, defined simply as securities not classified as either held to maturity securities or trading securities[2] (FASB 1993). Unrealized gains and losses on AFS securities are included in accumulated other comprehensive income (AOCI), a component of shareholders equity that is excluded from Tier 1 regulatory capital via the AOCI filter. This is because Available for Sale securities are reported at fair value on the balance sheet but at amortized cost in the income statement. Prior to the AOCI filter removal, AFS was the dominant classification choice for two reasons: (1) securities classified as such faced no sale restrictions, and (2) their fair value fluctuations were excluded from regulatory capital via the AOCI filter. Thus, AFS provided both the regulatory benefits of HTM and the liquidity benefits of trading assets.

1.2 Fair value vs amortized cost

By now it should be clear that HFT securities are treated at fair value in both the balance sheet and income statement, AFS securities are measured at fair value in the balance sheet and at amortized cost in the income statement and HTM securities are accounted for at amortized cost in both the balance sheet and income statement. Before diving deeper into accounting complexities, let me briefly introduce you to the basic concept of fair vale and amortized cost. Understanding the difference between

[1]These tests are aimed at verify that the capital structure is stable given various stress-test scenarios and that Planned capital distributions, such as dividends and share repurchases, are viable and acceptable in relation to regulatory minimum capital requirements.

[2]The security types are the same for HTM, what change is the intent to hold them temporarily and to sell in the near term.

FV and AC is fundamental because it allow us to see how financial institutions choose to represent an asset or liabilities in the financial statements.

By choosing fair value, a financial institution achieve the maximum transparency possible, because the value of asset/liability that will be recorder on its balance sheet and the interest expenses on its income statement will always reflect the current market changes. The two most widely used definition of fair value see the fair value defined as:

- Net present value of expected future cash flows using current information about cash flow and current market interest rates ;
- Exit value, defined as the price that would be received to sell an asset or paid to transfer a liability in a orderly transaction between market participants at the measurement date..

In FAS 157, FASB chose the second definition of fair value and in paragraph 8, FASB defines the principal market as the market in which the reporting entity would sell the asset, or transfer the liability, with the greatest volume and level of activity. In paragraph 9, FASB also specify that the price in the principal market used to measure the fair value shall not be adjusted for transaction costs. If location is an attribute of the asset, the price in the principal market must include these costs.

However fair value is not always easily determinable, as it is the case with complex or illiquid financial instruments. In this case, FAS 157 provides a hierarchy of fair value measurement inputs, classifiable as:

- level 1: A firm has to use Level 1 inputs on the assumption that a quoted price in an active market provides the most reliable evidence of fair value. It shall be used whenever available;
- level 2: If observable prices are not available, the firm can value its assets based on Level 2 inputs, which are observable inputs other than quoted prices included in Level 1. Level 2 inputs are inputs such as quoted prices for similar but not identical assets or liabilities in both active and inactive markets, and inputs other than quoted prices such as interest rates and yield curves, credit risks, default risks, and other inputs that can be derived principally from observable market data by correlation or other means. Most importantly, a Level 2 input must be substantially observable for the full term of the asset or liability;

- level 3: to the extent that observable Level 2 inputs are not available, for example in situations in which there is little market activity for the asset or liability at measurement date, Level 3 inputs can be applied. These are the firm's own assumptions about how other market participants would price the asset or liability. To ensure that there is information that will enable financial statement users to assess the quality of inputs used to estimate these fair value measurements, the standard requires firms to disclose information, both quantitative information that shows how the fair value measurements are segregated based on the valuation inputs, and qualitative information that specifies the valuation techniques used to measure fair value.

Conversely, by choosing amortized cost, a financial institution is basically isolating the asset/liability from the market environment because the value of asset/liability that will be recorder on its balance sheet and the interest expenses on its income statement remain constant all over the holding period following a predetermined schedule.

Focusing our attention now on AFS securities, they are recognized at fair value on the balance sheet and at amortized cost in the income statement. Net income include:

- Interest revenue measured on an amortized cost basis using the effective interest rate;
- Credit loss expenses, or benefits, from reversible credit impairments;
- Realized gain/losses upon sale of the security;
- Irreversible credit impairment write-downs.

Regarding irreversible credit impairment write-downs, also defined "OTTI" (Other than temporary impairments), under ASC 320, a debt security is considered impaired if its fair value is less than its amortized cost basis. When a security is impaired, an entity must determine whether the impairment is other than temporary. To do so, the entity must first consider whether it intends to sell the debt security. The following factors, among others, may indicate that the intent to sell a security exists:

- the entity or its agent (a third party that manages the entity's securities portfolio) has approved the sale of the security;

- the entity directs its agent to sell the security, which is contingent on an event that is expected to occur;
- the security is part of a group of securities that the entity or its agent has identified for sale.

Only if an entity does intend to sell the security, or it is more likely than not that it will be required to sell an impaired debt security before recovery, an OTTI exists and the entity must record an impairment loss equal to the difference.

Moreover, as long as the financial institution hold these securities, unrealized gains and losses are recognized in OCI, thus not affecting the income statement. However upon sale of these AFS securities, previously unrealized gain and losses are treated as realized leading to a reclassification of the amounts of the now realized gains and losses from other comprehensive income to net income (this mechanism is often referred to as "Recycling", which is allowed under GAAP but not under IFRS).[3]

Firms and financial institution are required to keep track of the amortized cost basis and effective interest rates for AFS securities, in order to determine amortized cost interest revenue, realized gain/losses and credit allowances for non reversible impairments. To do this, the fair value on AFS securities is broken into:

$$Fair\,Value\; = Amortized\,cost\,basis{-}credit\,loss\,allowance \pm valuation\,accounts$$[4]

1.3 Reclassifying from AFS to HTM

FAS 115 restricts firms from selling/reclassifying HTM securities except for:

- Major acquisitions by the firm, requiring rebalancing of the combined securities portfolios;
- Severe credit declines of the securities;
- Tax law changes affecting the tax status of the securities;
- Extremely remote disaster scenarios (including COVID-19).

Furthermore, the Federal Reserve set a limit to the reclassification from AFS to HTM, the latter of which cannot be more than 25% of Tier1 Capital. The actual

[3] Banks may engage in Gains Trading, which refers to the practice of selling securities with high unrealized gains in order to compensate for shortfall in profitability due to realized losses deriving from the forced sale of other securities.

[4] To account for non credit cumulative unrealized gain or losses.

regulation from Section.II.B.3 of Federal reserve's Capital Adequacy Guidelines for State Member banks: Risk-based measures (12 CFR Part 208, Appendix A) read as follow: Holdings of securities in the HTM category are subject to a separate limit of 25 percent of Tier1 capital, with the exception that securities issued by states, or political subdivisions of states, or any agency or instrumentality thereof are not subject to the 25 percent limit if they are investment grade and if the issuer has the authority to levy taxes or other revenues for the payments of principal and interest on the securities.

Transfers are accounted for at fair value in the following ways:

- if trading securities are transferred from AFS to HTM, then the fair value at time the time of transfer becomes the amortized cost basis of the security (see the T-account below)
- accumulated other comprehensive income at the time of transfer is accreted over time as if the security has remained AFS. This accretion renders future interest revenues unaffected by the transfer even though the amortized cost basis changes upon the transfer (for a numerical example, please see Appendix A).

Table 1.1: Using the Carrying Value to shows the passage from AFS to HTM

Carrying Value of AFS Securities

Beginning balance (fair value)	
+ purchases	- principal receipts
+ interest revenue	- interest receipts
+ total (realized+unrealized, credit and non credit) net gain during period	- sales (fair value)
= ending balance (fair value)	

Accumulated OCI on AFS Securities

	Beginning cumulative net unrealized non credit gain
- realized net non credit gain during period	+ total net non credit gain during period
	= ending cumulative net unrealized non credit gain

Carrying Value of HTM Securities

Beginning balance (amortized cost)	- principal receipts
+ purchases	- interest receipts
	- sales (amortized cost)
	- irreversible impairments of AFS securities
	- write offs of AFS and HTM securities
= ending balance (amortized cost)	

1.4 Basel III Capital Requirements

Basel III is a framework that sets international standards for bank capital adequacy, stress testing, and liquidity requirements and it is intended to strengthen bank capital requirements by increasing minimum capital requirements, holdings of high quality liquid assets, and decreasing bank leverage. Banks use different forms of capital to absorb losses that occur during the regular operations of the business and the main forms of capital that are included in the capital structure include Common Equity Tier 1 Capital (CET1 or Core Tier 1), Tier 1 Capital, and Tier 2 Capital.

- CORE TIER I = $\begin{array}{l}\text{Common shares plus/minus}\\ \textit{Retained earnings}\\ \textit{Reserves}\end{array}$

which divided by Risk Weighted Assets (RWAs) must be at least 4.5%,

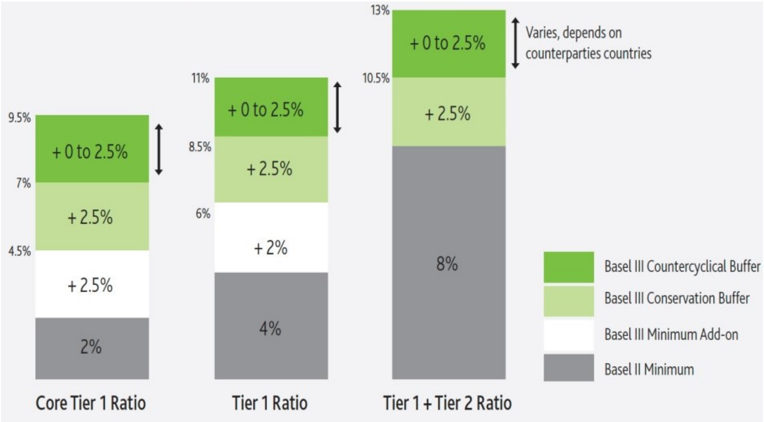


Figure 1.1: Regulatory Capital

- TIER I = Gaap Common Shareholder Equity plus/minus
  Goodwill and most intangibles
  AOCI reserves for AFS debt securities and derivatives
  Some pension plan net assets
  Certain assets in excess of prescribed limits

- TIER II = TIER I Capital plus/minus
  Cumulative perpetual preferred stocks
  Hybrid securities and perpetual debt
  Allowances for loan losses
  Unrealized gains in AFS securities

Fig.1.1 shows how the Basel III reforms actually improved and heightened the amount of capital the banks are required to maintain to guard against unexpected losses.

The capital conservation buffer was introduced to ensure that banks have an additional layer of usable capital that can be drawn down when losses are incurred. The buffer was implemented in full as of 2019 and is set at 2.5% of total risk-weighted assets and it must be met with Common Equity Tier 1 (CET1) capital only. Whenever the buffer falls below 2.5%, automatic constraints on capital distribution (for example, dividends, share buybacks and discretionary bonus payments) will be imposed so that the buffer can be replenished. The counter-cyclical capital buffer aims to protect the banking sector from periods of excess credit growth which potentially increases banks exposure to systemic risk.

Other complementary ratios introduced by the Basel Committee with Basel III regulation include the Liquidity Coverage Ratio (LCR), the Supplementary Leverage Ratio (SLR , also called Total Leverage ratio) and the Net Stable Funding Ratio (NSFR).

$$LCR = \frac{\text{High Quality Liquid Assets (HQLA)}}{\text{Total Net Cash Flow amount}} > 100\%$$

where the denominator's liquidity refers to a 30-day stress period.

$$SLR = \frac{TIER1\ Capital}{Total\ Leverage\ Exposure} > 3\%$$

Where the denominator includes an estimates of off-balance sheet asset exposures. The difference between the two above-mentioned ratios is that SLR is a constraint on the size of a bank's balance sheet, the LCR is a constraint on its composition.

$$NSFR = \frac{\text{Available amount of Stable Funding}}{\text{Required Amount of Stable Funding}} > 100\%$$

Differently from LCR, NSFR time horizon is one year.

Within the context of this research, Basel III regulation plays a pivotal in two and apparently contradictory ways. Firstly by the means of the well known AOCI filter. Established in 1995, this filter enabled banks not to consider the unrealized gains and losses in the regulatory capital thus giving banks more freedom in risk management and asset-liabilities management by reclassifying securities as AFS. However in 2014 U.S. bank regulaotrs began the phased removal of the AOCI filter only for AA banks and for all non AA banks who voluntarily opted to do so, thus drastically changing the banking environment. With the removal, all the unrealized gains and losses on AFS flow directly into the regulatory capital, making it extremely volatile especially during crisis when banks need to be as much solid as possible.

Secondly, the Basel III capital rules provide more favorable capital treatment for securities held in the HTM category compared to those held in the AFS category. This due to the fact that under Basel regulation, banks account for credit risk by using two different approaches: Standardized and Advanced, also known as IRB (internal rating based). The standardized approach is a simpler method that applies standardized risk weights to various types of assets based on their credit ratings or other characteristics. The standardized risk weights are determined by regulators and apply to all banks using this approach. Banks using the standardized approach generally have less discretion in determining their capital requirements. In contrast, the IRB approach allows banks to use their own internal risk models to calculate the probability of default (PD) and loss given default (LGD) for their various exposures. This allows for greater differentiation in risk weights, with riskier exposures requiring higher capital charges. Also,banks that use the IRB approach must obtain regulatory approval for their internal risk models. However, under the Internal Ratings-Based (IRB) approach, securities held in the banking book, including both Held-to-Maturity (HTM) and Available-for-Sale (AFS) securities, are subject to different capital requirements: in general, HTM securities are given preferential treatment over AFS securities with respect to credit risk because they are assumed to be held until maturity and thus are not subject to fluctuations in market value. As a result, HTM securities are treated as having a lower credit risk than AFS securities. Under the IRB approach, the risk-weight for HTM securities is typically lower than that of AFS securities with the same credit rating. This means that banks need to hold less capital against their HTM securities than they do against their AFS securities.

Chapter 2

Literature and Assumptions

The purpose of this research is to study and shows how changes in interest rates influence banks choice to reclassify securities more from AFS to HTM and the subsequent effects of these reclassification on the regulatory capital of financial institutions. Therefore, I thought to organize this section of my thesis in two parts. The first part concerns the literature review, which is divided in three macro-categories: an introduction of historical background about the origins of fair value accounting and amortized cost, in which is also documented how the FASB acted toward markets anomalies by issuing regulations some of which are still in use today. Then I propose a literature review focused more on fair value and amortized cost. In particular I tried to shed more light on the conflicts between proponents of fair value versus amortized cost, by documenting the reasons behind the preference for one criteria or the other. At last but not least, for this is the part more linked to my research, I dive deeper into the sub-field of fair value/amortized cost by presenting the literature concerning the AOCI filter removal and its effects on the AA banks. The second part regards the assumptions I made while developing my analysis..

2.1 Related literature

Historically, a significant financial event or crisis has often served as a stimulus for a reconsideration of the accounting rules governing reported assets valuations. The credit crisis of 2008 has generated calls for such a reconsideration of accounting rules, and the SEC report specifically mentions as past catalysts the Great Depression, the market decline of 1973 and 1974, and the savings and loan crisis of the 1980s. Prior to the Great Depression, and thus prior to the establishment of the SEC, firms had flexibility about reporting asset valuations. In practice, firms revalued assets both up and down. Researcher examined SEC filings from a random sample of 208 NYSE firms. and found that 75% of the firms in the sample had written asset values either up or down, with write-downs substantially exceeding write-ups. Thus, it appears that asset revaluations were fairly common prior to 1934. Warried about uncontrolled accounting manipulations, the SEC essentially forbade upward revaluations of assets, and favoured historical cost accounting. By 1940, upward revaluations were rare. The savings and loan crisis "S&L") of the 1980s provided another impetus to move away from strict historical cost accounting. Banks that had made long-term mortgage loans and borrowed short-term suffered severe economic losses when interest rates increased. A fair value accounting system would in principal have made these losses obvious, but with historical cost accounting and the resulting emphasis on realization, S&L losses took years to be formally recognized. Finally, the introduction of financial derivatives in the 1970s and the 1980s required changes in accounting rules. Financial futures allowed firms to take zero-investment positions that could quickly accrue large gains or losses and there were no accounting standards recognizing the new character of these contracts. In response, SFAS 52 and 80 required fair value accounting for foreign exchange contracts and futures contracts not used in hedging. At the time the FASB began the project on financial instruments mark-to-market accounting was common place for assets held in trading accounts. The problem the FASB faced was whether and how to generalize the trading account treatment to assets held for other purposes. SFAS 107 (FASB, 1991) required "all entities to disclose the fair value of financial instruments, both assets and liabilities recognized and not recognized in the statement of financial position, for which it is practicable to estimate fair value SFAS 115 (FASB, 1993) created the basic accounting structure for "debt and equity securities, but explicitly not for unsecuritized loans, that is still in use today. Specifically, SFAS115 states: debt securities that the enterprise has the positive intent and ability to hold to maturity are classified as held-to-maturity securities and reported at amortized cost. Debt and equity securities that are bought and held principally for the purpose of selling them in the near term are classified as trading securities and reported at fair value, with unrealized gains and losses included in earnings. Debt and equity securities not classified as either held-to-maturity securities or trading securities are classified as available-for-sale securities and reported at fair value, with unrealized gains and losses excluded from earnings and reported in a separate component of shareholders' equity. The separate component of shareholders equity is reported on balance sheet under "other comprehensive income" (OCI). The category was designed to reconcile stocks and flows but at the same time keep certain flows separate from earnings. The unrealized gains and losses in OCI are reported in earnings if the asset is sold. There is also another circumstance in which OCI is realized and incorporated in to earnings: for individual securities classified as either available-for-sale or held-to-maturity, an enterprise shall determine whether a decline in fair value below the amortized cost basis is other than temporary. If the decline in fair value is judged to be other than temporary, the cost basis of the individual security shall be written down to fair value as a new cost basis and the amount of the write-down shall be included in earnings as a realized loss. SFAS 157 (FASB, 2006) defined fair value as the "price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date. The statement created a hierarchy of valuations: Levels 1, 2, and 3, defined as prices observed in the market (level1), based upon inputs observed in the market (level2), and with unobservable inputs (level3). This is sometimes described as mark-to-market, mark-to-matrix, and mark-to-model. Important in the definition of fair value is the notion of an orderly transaction. Forced liquidations and distressed sales are mentioned as examples of non-orderly transactions. The FASB, In April 2009, provided criteria for firms to use in assessing whether markets are orderly and transactions are distressed. We discuss this below. This ruling was seen as giving banks flexibility in avoiding downward revaluations during the credit crisis. Finally, SFAS159 (FASB, 2007) expanded the range of assets that could receive fair value treatment. For example, under 159, it is possible to use fair value for available-for-sale assets, and gains and losses on these assets would then flow through the income statement. SFAS 159 also permitted firms to mark their own liabilities to market, a somewhat controversial provision that would permit a firm with bond prices falling due to deteriorating credit, to realize a gain. The statement allowed the firm to elect fair value treatment on individual classes of options.

Relating now to the academic debate regarding preferences over amortized cost versus fair value accounting methods**,** in Christian Laux (2009)argued that the role of mark-to-market (MTM) during the recent financial crisis has generated an intense debate. Critics argue that FVA, often also called mark-to-market accounting (MTM), has significantly contributed to the financial crisis and exacerbated its severity for financial institutions in the U.S. and around the world. On the other extreme, proponents of FVA argue that it merely played the role of the proverbial messenger that is now being shot (Turner, 2008; Veron, 2008). In their view, there are problems with both positions. FVA is neither responsible for the crisis nor is it merely a measurement system that reports asset values without having economic effects of its own. Moreover, the concern about the downward spiral is most pronounced for FVA in its pure form but it does not apply in the same way to FVA as stipulated by U.S. GAAP or IFRS. Both standards allow for deviations from market prices under certain circumstances (e.g., prices from fire sales). Thus, it is not clear that the standards themselves are the source of the problem. However, they discovered that there could be implementation problems in practice. It is far more important, in the authors view, to recognize that accounting rules interact with other elements of the institutional framework which could give rise to unintended consequences. For instance, they point out that managers' concerns about litigation could make a deviation from market prices less likely even when it would be appropriate. Concerns about SEC enforcement could have similar effects. At the same time, it is important to recognize that giving management more flexibility to deal with potential problems of FVA in times of crisis also opens the door for manipulation. For instance, managers could use deviations from depressed market values to avoid losses and impairments. The same reasults are reached by John C. Heaton (2010). His analysis shows that some of the problems that arise with the introduction of fair value accounting are not due to the accounting rule in itself, but rather from the interaction of fair value accounting and the definition of capital requirements. Over time capital requirements are periodically revised by bank regulators, as is the FASB's definition of capital, but the two types of regulatory actions are not coordinated. In fact the recent trend toward more comprehensive fair value accounting does not seem to have been accompanied by a rethinking of capital requirements and how they should be harmonized with a fair value accounting regime. On the same line, ELLUL et al. (2015) provide empirical evidence concerning the contentious debate over the use of historical cost versus fair value accounting in regulating financial institutions. These accounting rules, through their interactions with capital regulation, alter financial institutions' optimal portfolio choice and trading behavior. The theoretical literature on this subject (Allen and Carletti (2008), Plantin, Sapra and Shin (2008), and Sapra (2008)) argues that during times of market stress, when markets are illiquid and trading frictions elevated, mark-to-market (MTM), or fair value, accounting leads to financial assets temporarily trading at market prices that are well below fundamental values. In such an environment, write-downs, and the associated deterioration of financial institutions' asset values, will lead to an erosion of their capital base, potentially forcing the liquidation of some assets. Allen and Carletti (2008) argue that in such a market environment, HCA will avoid fire sales and thus contagion effects because financial institutions would not suffer from a deterioration of their asset valuations in the first place. This paper challenges this view by providing empirical evidence that historical cost accounting, along with regulatory capital requirements, induces an altered incentive to gains trade where, in order to shore up capital, an institution selectively sells otherwise unrelated assets with high unrealized gains in order to more than compensate the realized losses deriving from the forced selling of securities. Moreover, lack of transparency under HCA could make matters worse during crises. These problem connected with historical accounting was well known even before the 2008 crisis. Beatty (1995) documents how, in a 1990 letter, the SEC lobbied accounting rule makers to require financial institutions to use market values when accounting for securities investments.The letter argued that historical cost accounting produces information that is irrelevant to valuing investment portfolios and provides an opportunity for managers to manipulate the numbers reported in financial statements. Yuan and Liu (2011) argue that fair value has conceptual flaws. In their paper, the authors prove that if the total supply of the asset is larger than equilibrium trading volume, the fair value for the asset does not exist anymore. This in turn creates the so called “fair value trap”. In practice, many firms may not want to sell out all their assets, like financial assets and real estates, but continue to hold them for better profit. A direct result of the decision is that the current market price could be maintained at a level higher than the clearing price at which all existing assets could be sold. If the market price is taken as a reliable evidence of fair value and the assets are measured based on mark to market accounting, a large income from changes in fair value may be recognized. It can be regarded as a fair value trap because it cannot be changed into cash flow in the present circumstances in the near future. Bischof et al. (2023) examine the introduction of the reclassification option for financial assets during the 2008 financial crisis and study the position of accrual-based options (reclassification from AFS to HTM) in the pecking order of banks' recapitalization measures. The findings suggest that the accrual-based increase in regulatory capital is temporary and does not provide permanent relief. Consistent with the long-term costs of accrual-based measures, investors perceive the accounting choice as a negative signal. If banks do not complement their use of the accounting option by other corrective actions that result in a real capital increase and a liquidity injection, they continue to suffer from low capitalization and financial difficulties in the following years. However capital injection is not always perceived as positive. Capital injections imply a transfer of control rights to new shareholders and, if capital is injected through a bailout, to government agencies. Shareholders perceive the dilution of their existing position as a cost of the recapitalization strategy that the concurrent use of equity-increasing accrual-based measures can help minimize. The cost is generally reflected in negative market reactions to new equity issuances (Cornett and Tehranian 1994, Cornett et al. 1998). In the case of a bailout, the loss of control rights also manifests in government influence on future investment and risk policies or limits to executive compensation, which can significantly impact bank value. Kevin Ow Yong (2009) move even further by studying and analyzing the role of capital adequacy and audit quality in influencing investors' pricing of the fair value assets at each one of the three level (Level 1, 2, 3 Fair value). In particular, they observed a pronounced decline in the pricing of each dollar of Level 2 and Level 3 assets from the first to the third quarter of 2008. In contrast, the pricing of each dollar of Level 1 assets remains relatively stable over the course of 2008. Specifically, for each dollar of Level 2 (Level 3) assets reported by the banks, the pricing by investors decreases by 30.6 (56.9) percent. In contrast, the pricing of each dollar of Level 1 assets increases by 19.6 percent. Overall, these results suggest that liquidity and information risk are two factors driving investors' pricing of fair value assets. Also, an interesting result is that the pricing of Level 3 assets is only significantly greater than zero for banks with higher capital adequacy and better auditors. Bergheim (2014) paper investigates how fair value measurements of financial instruments affect the decision of nonprofessional investors to invest in a bank's shares. Specifically, the authors assess how investors respond to variations in net income resulting from fair value adjustments in trading assets and how the reliability of the fair value estimates affects their decision. The findings support that investment decreases as a result of transitions from the first to the third level and that investment decreases most if negative valuation adjustments are based on level 1 estimates suggesting that down pricing by the market is considered as a worse signal than model-based decreases in net income.

Finally, relating to the AOCI filter removal, the U.S. bank regulators imposed the AOCI filter in January 1995, approximately one year after FAS 115's effective date. The filter excludes most items recorded in accumulated other comprehensive income, most importantly, unrealized gains and losses on AFS securities, from regulatory capital. Prior research suggests that the filter, on average, reduces banks' regulatory capital volatility (Barth et al. 1995). The filter has minimal effect on HTM securities, and it eliminates regulatory capital-based incentives for banks to classify securities as HTM rather than as AFS. Basel III eliminates the AOCI filter. U.S. bank regulators initially proposed to remove the filter for all U.S. banks. Their stated rationale was to remove incentives for banks to delay selling depreciated AFS securities. The banking industry lobbied against the proposed rule, claiming that the filter removal would ignore banks' use of AFS securities in asset-liability management and, thus, exaggerate the impact of interest rate changes, leading banks to reduce the duration of AFS securities; would increase the volatility of banks' regulatory capital, rendering capital planning more difficult; and would require banks to increase regulatory capital buffers, reducing lending. U.S. bank regulators accepted these concerns for most banks, as the Final Rule removes the AOCI filter only for AA banks. The filter removal provides a regulatory capital-based incentive for AA banks to classify securities as HTM rather than as AFS. The final rule phases in the filter removal over a five-year period beginning on January 1, 2014, so the incentive increased from 2014 to 2018. It allowed non-AA banks to irrevocably choose to retain the filter by March 31, 2015. Almost all non-AA banks made this choice. The removal of the AOCI filter plays a fundamental role in the scope of my thesis: changes in interest rates strongly affect the unrealized gains/losses of AFS which in turns affects the equity of the banks and thus the regulatory capital. Therefore, banks are strongly incentivised to exploit the reclassification of securities from AFS to HTM. Nonetheless, this transfer strongly limit the liquidity of fixed-income markets and constrain banks' market making capacity. Kim et al. (2019) examine the economic consequences deriving from the removal of the filter. They found that, to mitigate regulatory capital volatility resulting from the filter removal, advanced approaches banks increased the proportion of investment securities classified as held-to-maturity, thereby limiting their financing and interest rate risk management options, and they decreased securities risk, therefore reducing their interest rate spread. Moreover, they found that these banks borrow more under securities repurchase agreements potentially collateralized by held-to-maturity securities and reduce loan supply due to to their reduced financing options, and that they increase loan risk to mitigate the decrease in their interest rate spread. Hamilton (2019) study provides a very helpful insight on the reduced markets liquidity caused by the filter removal. He found that the predicted increase in HTM classification necessarily reduces the liquidity of banks' balance sheets and, more specifically, their fixed income portfolios. However, active portfolio management is an indispensable part of fixed income market making, and a reduced ability to do so is the cost banks accept in the HTM classification trade-off. More in detail, he discovered that agency RMBS are more frequently classified as HTM than agency CMBS, Fannie Mae and Freddie Mac RMBS are more frequently classified as HTM than Ginnie Mae RMBS, and traditional RMBS are more frequently classified as HTM than interest-only collateralized mortgage operations (CMOs). At the annual American banker association meeting in 2012, the senior associate director Lindo (2012) documented the whole discussion concerning the Basel III removal of the existing filter of certain unrealized gains and losses on financial instruments (the "AOCI Filter") from regulatory capital components. What emerged from the meeting is that the removal of the AOCI filter is expected to cause banks to shorten the duration of their investment portfolios, with consequences for the markets for 30- year mortgages, longer-term U.S. treasury bonds and municipal securities. In order to minimize the magnitude of unrealized gains and losses from AFS Securities, and the resulting impact from AOCI that, with the removal of the filter, will impact regulatory capital, banks likely will, and some have begun to, shorten the duration of their investment securities portfolios. The fair market value of debt securities with shorter duration is less sensitive to changes in interest rates than that of long-term debt securities. In a rising interest rate environment, the resulting unrealized losses from a shorter duration portfolio will have less of an impact on a bank's regulatory capital. Also another point that is worth considering is that removal of the AOCI filter will negatively impact banks' regulatory capital in a rising interest rate environment, which will decrease the ability of banks to lend and to contribute to any related economic recovery through the extension of credit. This is basically caused by incurred unrealized losses recorded in AOCI as banks mark AFS Securities to market. As regulatory capital across the banking industry is impacted, the lending capacity of the industry will be affected as well. On the same path Fuster and Vickery (2018) research suggest that there has been a significant decrease in security duration for AOCI banks, although their total duration risk exposure does not decrease over the same period. They also found an increased use of derivatives to hedge securities exposures. Most importantly though, they found significant evidence that treated banks respond to the filter removal by actively reshuffling their portfolios, and in particular classifying risky securities as held to maturity rather than available for sale and that this reshuffling specifically concerns MBS and Treasury securities with higher duration. Although reclassifying securities in this way reduces the volatility of regulatory capital, it does not mitigate the fundamental risks of the assets held. Given that there are obstacles to selling securities classified as held-to-maturity (the so called tainting rule), such reclassification may in some circumstances even increase risk, to the extent that it reduces the liquidity of the bank's assets during periods of stress. As mentioned above, before the AOCI filter removal, banks were used to manipulate earnings by engaging in "gains trade" transactions, by deliberately selling AFS with high unrealized gains. However since the removal of the AOCI filter this strategy no longer an effective tool to increase regulatory capital. Therefore in their study, Zhao and Deis (2020) argue that advanced approaches banks might deliberately understating loan loss provisions to increase earnings. Surprisingly though, they found that advanced approach banks do not deliberately understate more loan loss provisions to boost earnings in the phase-in period than in the pre-period. However, they also found that non advanced banks begin to deliberately understate loan loss provisions to manipulate earnings but no longer to manipulate regulatory capital ratios in the phase-in period. Departing a little from the AOCI filter removal, but still within the realm of Basel III, Cimon and Garriott (2020) discuss that Basel III regulations (following FAS157) deeply affected the structure of securities market, by forcing a shifting from principal-based to agency-based structure. While these regulations are designed to prevent crises in banking, they may also create unintended costs for financial markets. Specifically, the regulations may constrain the ability of banks to buy and sell securities for their clients, which is a necessary financial service. The conventional business of a bank is to borrow money at short terms and invest it at long terms. In addition to this, many banks also operate a securities dealer, which is not in the business of investing in the conventional sense. Securities dealers buy and sell securities for distribution to clients, not for investment. Yet Basel III regulates their securities positions as if the dealer were intending to hold its securities to maturity, with obvious consequences on regulatory capital. The regulations motivate dealers to use an agency basis of market making. In agency market making, a securities dealer matches an investor who wants to trade with someone else who will agree to take the other side. This contrasts with the usual basis of market making, the principal basis, in which a dealer itself takes the other side of the trade and holds the position on its balance sheet. However, greater stability of banks comes at a cost to investors: the price required to motivate investors to trade with one another adds needless frictions and price impact that did not exist before. Following the same path, Gup and Lutton (2009) examine what happens to banks if interest rates change unexpectedly. Their founding support that in a rising interest rate environment, the fair value of the long-term assets held for sale will decline more than the fair value of the shorter-term liabilities resulting in a decline in fair value of the bank's equity capital. If banks do not hedge with derivatives or match the maturities of their assets and liabilities may be at risk of being under capitalized in a rising interest rate environment.

2.2 Assumptions

As we can see the literature on the topic has old roots and is well articulated as all the facets of the fair value versus amortized cost trade-off are analyzed and discussed. My research is closer to the latter school of thought. However I depart from it a bit as I am not trying to demonstrate the effects of the AOCI filter removal but instead I take these effects for granted while developing my own model, with which I tried to study what are the variables that influence the decision of banks to reclassify more under HTM than AFS. In doing so I divided my analysis in three time frames: "before Covid", "during Covid" and "post Covid". I did so as from beginning of the Covid period to the end of post Covid, the macroeconomic policies of central banks changed dramatically, switching from ultra-low interest rates environment to balloon-size interest rates increases to tame inflation. Moreover by comparing these two periods with the "before Covid" period, I think I will be able to spot for changes in behavior from banks. In summary I assume interest rates to have a direct and strong relationship with the choice to reclassify more as HTM over AFS, due to the fact that interest rates strongly influence the present value (PV) of the securities, thus prompting unrealized gains and more importantly unrealized losses that can severly impact the performance and prompt regulatory capital violations.

Chapter 3

Do interest rates changes lead banks to reclassify more under HTM?

3.1 Data and sample size

The data I used for my analysis come all from the same source, as I mainly used the National Information Center platform[1] , a repository of financial data collected by the Federal Reserve system. I did so in order to minimize data discrepancies that using data from different sources may imply. However, it must be noted that the above-mentioned database only contains the latest financial quarters, spanning from the last quarter of 2022 to the first quarter of 2018. For all the older data, I had to use the archives of the same website, which however from time to time didn't closely match. Therefore, in order to reduce the discrepancy I used the official quarterly reports available on the banks website. Regarding the interest rates, I used the FRED series "3 months Treasury bill secondary market rate"[2] as a proxy for interest rates on the markets and as inflation rate I used the FRED series "Inflation, Consumer prices for the United Stated" [3].

Regarding the sample size, I analzyed the 11 banks defined by the FED as Advanced Approach (AA banks). This is because only for AA banks the removal of the AOCI filter removal apply. For all the non-AA banks there is no point in reclassifying under HTM as they can achieve the same benefits by simply keeping the securities they don't want to sell in the near future as AFS. The 11 banks I analyzed are namely: Bank of America ("BAC"), Citibank ("C"), Citizensbank ("CFG "), HSBC("HSBA"), JPMorgan Chase & Co ("JPM"), Morgan Stanley ("MS"), BNY Mellon ("BK"), Statestreet ("STT"), UsBancorp ("USB"), Wells Fargo ("WFC").

[1] https://www.ffiec.gov/NPW

[2] https://fred.stlouisfed.org/series/TB3MS

[3] https://fred.stlouisfed.org/series/FPCPITOTLZGUSA

3.2 Methodological approach

While prior research and studies mainly used the DiD (difference-in-differences) approach, in my analysis I used linear regressions. This does not come as ease at use, but simply because DiD is irrelevant in my analysis. While past research's (e.g. Kim et al. (2019)and Hamilton (2019)) core topic was to show how the removal of the AOCI filter removal impacted the reclassification for AA banks, in my analysis I gave this result for granted and I did a further step forward by analyzing the underlying variables (e.g. interest rates and other variables) that brought banks to use HTM over AFS reclassification in periods of market stress. Therefore we can clearly understand that DiD regression in my study is not useful as I am not trying to measure the effects of a particular regulation but instead I used the result of previous research as a basis to build-up my own model. As a result I analyzed the 11 above mentioned banks during three time frames: before crisis (01-03-2014 to 31-12-2019) during Covid (01-03-2020 to 31-12-2021) and post Covid (01-03-2022 to 31-12-2022), sometimes referred to also as both dummies period. The off-spring of this analysis is comprehensive of 33 linear regressions plus 3 macro-regressions, as I wanted to see not only the bank-wise effects but I also wanted to have a broad and general picture of how the AA's banking landscape behave during the period of study.

3.3 Hypothesis and findings

H1. *: Variation in interest rates causes banks to reclassify securities more under HTM than AFS.*

The reasoning behind this first hypothesis is that, economically speaking, changes in interest rates are known to affect the market value of securities, so that I expect some kind of relationship between interest rates and HTM security reclassification. To see and study that, I thought at first to regress:

- Interest rates against
- HTM [4] (dependent variable during all my analysis)

before Covid, so as to see how this relationship behaves in times of normal market conditions. Mathematically this simple regression can be written as:

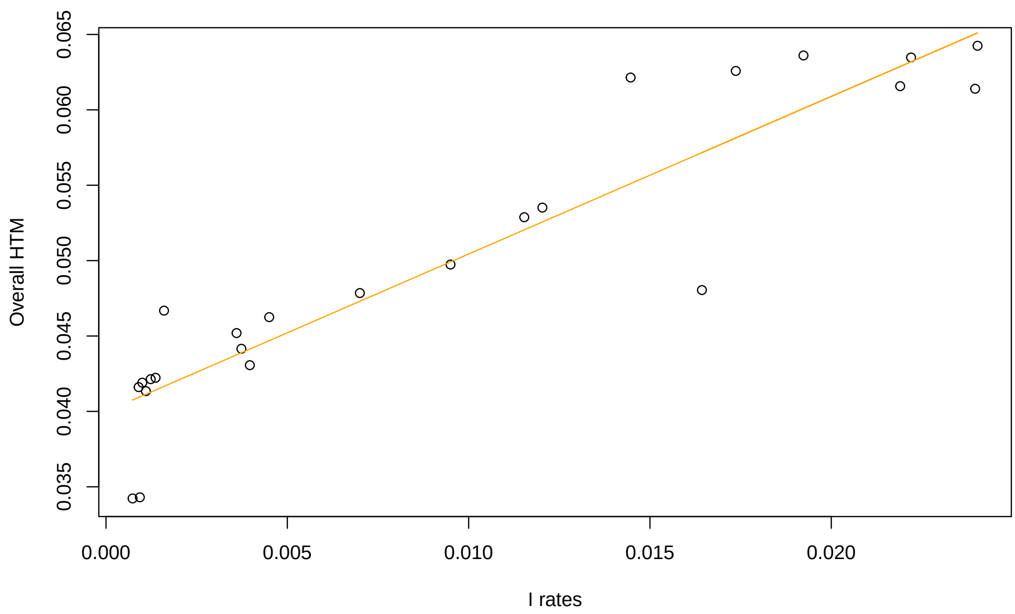
[4] An in depth disclosure of how I calculated each variable will be presented shortly in the Appendix for your reference

$$\hat{Y} = \alpha_0 + \beta_1(Irates) + \varepsilon i$$

where Y represent my dependent variable HTM securities. Below you can see both the output of the regression and the graph showing this relationship:

```
##
## Call:
## lm(formula = `Overall HTM` ~ `I rates`, data = spline1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0091144 -0.0009094  0.0006141  0.0010747  0.0070378
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.039988   0.001138   35.14  < 2e-16 ***
## `I rates`   1.045112   0.090852   11.50 8.91e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.003711 on 22 degrees of freedom
## Multiple R-squared:  0.8574,Adjusted R-squared:  0.851
## F-statistic: 132.3 on 1 and 22 DF,  p-value: 8.912e-11
```

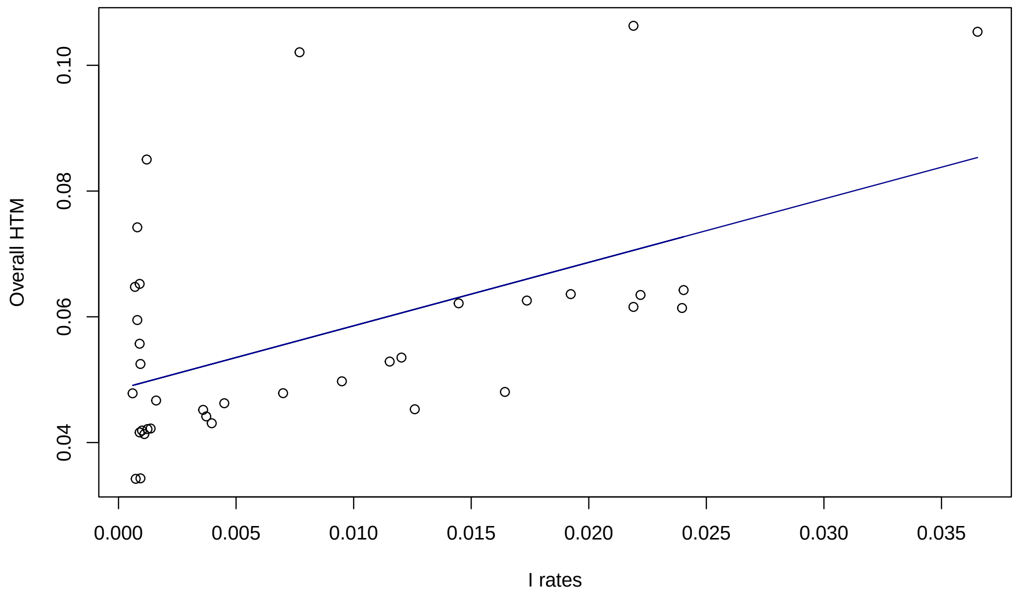
Figure 3.1: Relationship HTM ~ I rates in times of normal market conditions



As we can see from the graph and more in detail from the output table, during times of markets tranquility, I rates are a good predictor of HTM movements, with a Multiple R-squared of 85.74% and an Adjusted R-squared of 85.1% with a t-stat value of 8.91e-11 at a significance level of 99%, indicating a strong relationship between the two variables. Also the sign of the interest rates variable is positive, indicating that the Covariance of HTM and I rates is positive, that is, the two variables tend to move in the same direction. Thus, this imply that during normal market times, a rise in interest rates brings banks to reclassify more under HTM than AFS, as the PV of the securities decreases, thus prompting unrealized losses have effects on the performance and regulatory capital of banks due to the removal of the AOCI filter. However this strong positive, linear relationship does not always holds. Interesting enough, I then regressed and plotted Overall HTM against I rates considering also periods of market stress, such as Covid and post Covid periods, and I found that this strong relationship does not hold anymore.

```
##
## Call:
## lm(formula = `Overall HTM` ~ `I rates`, data = spline1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.017011 -0.008264 -0.007171  0.003888  0.045832
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.048479   0.003574  13.565 2.81e-15 ***
## `I rates`   1.008951   0.281465   3.585  0.00105 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01576 on 34 degrees of freedom
## Multiple R-squared:  0.2743,Adjusted R-squared:  0.2529
## F-statistic: 12.85 on 1 and 34 DF,  p-value: 0.001046
```

Figure 3.2: Relationship HTM ~ I rates in times of market stress

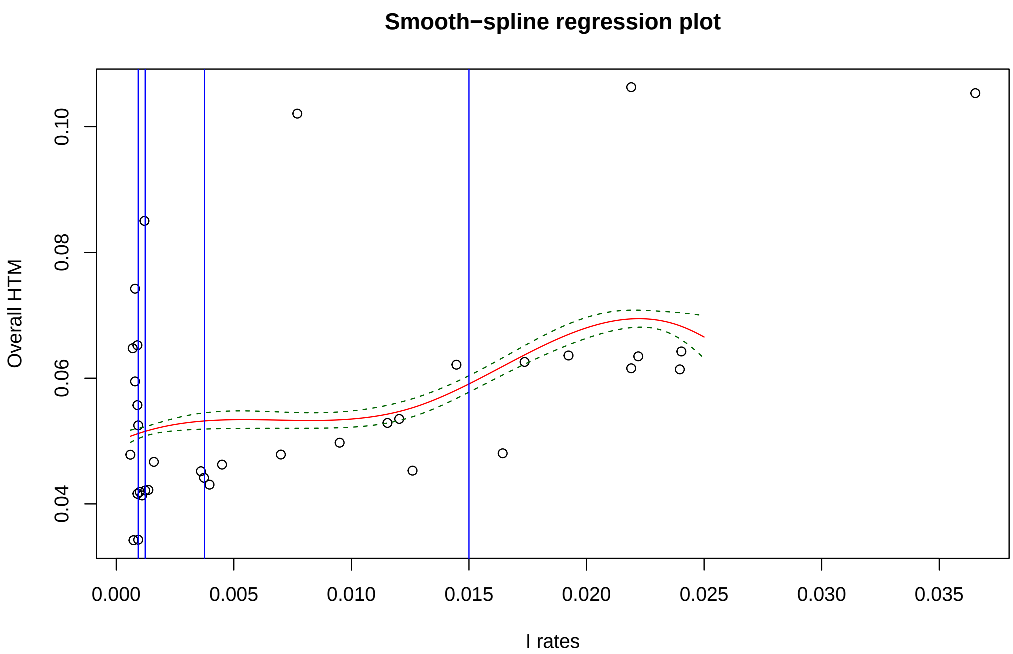


From the summary output, the test statistics are well below, with a Multiple R-squared at just 27% and an Adjusted R-squared of 25% with a t-stat value of 0.00105, which is still significant at a 95% confidence level. The Covariance sign is still positive, indicating a positive relationship. However it is clear now that interest rates alone are no longer effective in explaining why banks decides to undergo the reclassification during periods of stress. Therefore I tried to see if there were still some kind of non linear relationship between Overall HTM and I rates, (e.g. Exponential, Logarithmic or Polynomial). Indeed I tried to compute and plot a smooth spline regression to spot for non linear relationship between the two variables. Below you can see the chart representing the Spline, a regression technique that divides the regression in knots (blue vertical lines) and inside these knots it performs polynomial regressions. A spline, thus, is the results of several polynomial regressions each one computed from knots to knots, put together.

```
##
## Call:
## lm(formula = `Overall HTM` ~ bs(`I rates`, knots = c(6e-04, 0.0126,
##     0.0239667)), data = spline1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.016891 -0.009379 -0.004619  0.001986  0.048797
```

```
##
## Coefficients: (1 not defined because of singularities)
##                                                    Estimate Std. Error t value
## (Intercept)                                         0.10534    0.01609   6.545
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))1 -0.05458    0.01682  -3.244
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))2 -0.04903    0.02335  -2.100
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))3 -0.06010    0.03020  -1.990
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))4 -0.01670    0.04456  -0.375
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))5 -0.07135    0.11954  -0.597
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))6       NA         NA      NA
##                                                    Pr(>|t|)
## (Intercept)                                        3.08e-07 ***
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))1  0.00289 **
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))2  0.04424 *
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))3  0.05572 .
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))4  0.71043
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))5  0.55510
## bs(`I rates`, knots = c(6e-04, 0.0126, 0.0239667))6       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01609 on 30 degrees of freedom
## Multiple R-squared:  0.3324,Adjusted R-squared:  0.2211
## F-statistic: 2.987 on 5 and 30 DF,  p-value: 0.0264
```

Figure 3.3: Smooth Spline regression HTM ~ I rates



However, even with a smooth spline the result does not improve significantly, with a Multiple R-squared of 33% against the 27% above and an Adjusted R-squared of 22% against the 25% above. It is clear therefore that during market stress periods, interest rates are not enough to explain the behavior of banks to choose HTM over AFS. As a result, I reverted back to the original linear regression, but this time I factored in other independent variables in order to get a better fit. The variables I decided to consider are the following:

- Net Interest Income ("NII") Volatility: it is the difference of interest income and income expenses and is a proxy of the profitability of the core business of a bank. I decided to include this variable in my model because it may be useful to monitor how the core business strategy of the bank influences the decision of reclassify more under HTM. More in detail I expect an increase in HTM when the NII volatility increases, as the banks might want to reduce risk of the securities in its portfolio;
- ROA: ROA allows me to monitor for the return of the banks assets. As the return on assets improve, banks' management may be incentivized to keep securities reclassified as AFS. However, as profitability slacks, management might transfer these securities to HTM so as to avoid marking them to market with obvious negative consequence on banks overall performance;
- Option-Adjusted spread on MBS: OAS on the Mortgage backed Securities allow me to control for the credit risk in the MBS market. I have chosen MBS, as I will show later, because Residential mortgage backed securities (RMBS) and Commercial backed securities (CMBS) are the mostly reclassified securities from AFS to HTM. Credit risk might play a pivotal role together with interest rates in explaining the behavior of banks. A high credit risk may deteriorate considerably the value of banks' portfolios, thus prompting them to switch reclassification of securities in order to avoid regulatory capital violations;
- Leverage: I decided to include leverage as well, as higher level of leverage may make it difficult for banks to absorb credit losses;
- Inflation rate: Including inflation rate on my analysis will allow me to control for macroeconomic changes that are not fully captured by inflation rate. Inflation is also particularly relevant in the time frame I considered, since from Covid crisis onward, inflation kept ramping up, with painful effects on the general economy.

Please refers now to AppendixB to see how I calculated each variable[5]. The variable I have chosen for my analysis seemed reasonable to me and statistically coherent and indeed the data shows, among other statistical tests, very little multicollinearity, indicating that the good fit (R squared) I got for my models is a genuine one since the good R squared is not given by independent variables explaining each other resulting in an "artificial" good fit. With these variables I performed a linear regression against the dependent variable "Overall HTM" during three different times frame as mentioned above: before Covid, during Covid and after Covid . I firstly performed the regression on the aggregate group of banks so as to have a broader, general picture and I then performed 33 regressions, one for each bank across 3 time intervals. Mathematically, the regression models can be written as follow:

$$\hat{Y} = \alpha_0 + \beta_1(Irates) + \beta_2(NII) + \beta_3(ROA) + \beta_4(OAS) + \beta_5(Leverage) + \beta_6(Inflation\ rate) + \varepsilon i$$

$$\hat{Y} = \alpha_0 + \beta_1(Irates) + \beta_2(NII) + \beta_3(ROA) + \beta_4(OAS) + \beta_5(Leverage) + \beta_6(Inflation\ rate) + \beta_7 Covid + \varepsilon i$$

$$\hat{Y} = \alpha_0 + \beta_1(Irates) + \beta_2(NII) + \beta_3(ROA) + \beta_4(OAS) + \beta_5(Leverage) + \beta_6(Inflation\ rate) + \beta_7 Covid + \beta_8 PostCovid + \varepsilon i$$

where Covid and Post Covid are two dummy variables. Now I will present here my findings, firstly under a statistical point of view, to which I will attribute an economical meaning later on.

```
##
## Call:
## lm(formula = `Overall HTM` ~ `I rates` + `Overall NII volatility` +
##     `Overall ROA` + `Overall Leverage` + `Inflation rate` + `OAS MBS spread`,
##     data = nodummiesfit1)
##
## Residuals:
##         Min         1Q     Median         3Q        Max
```

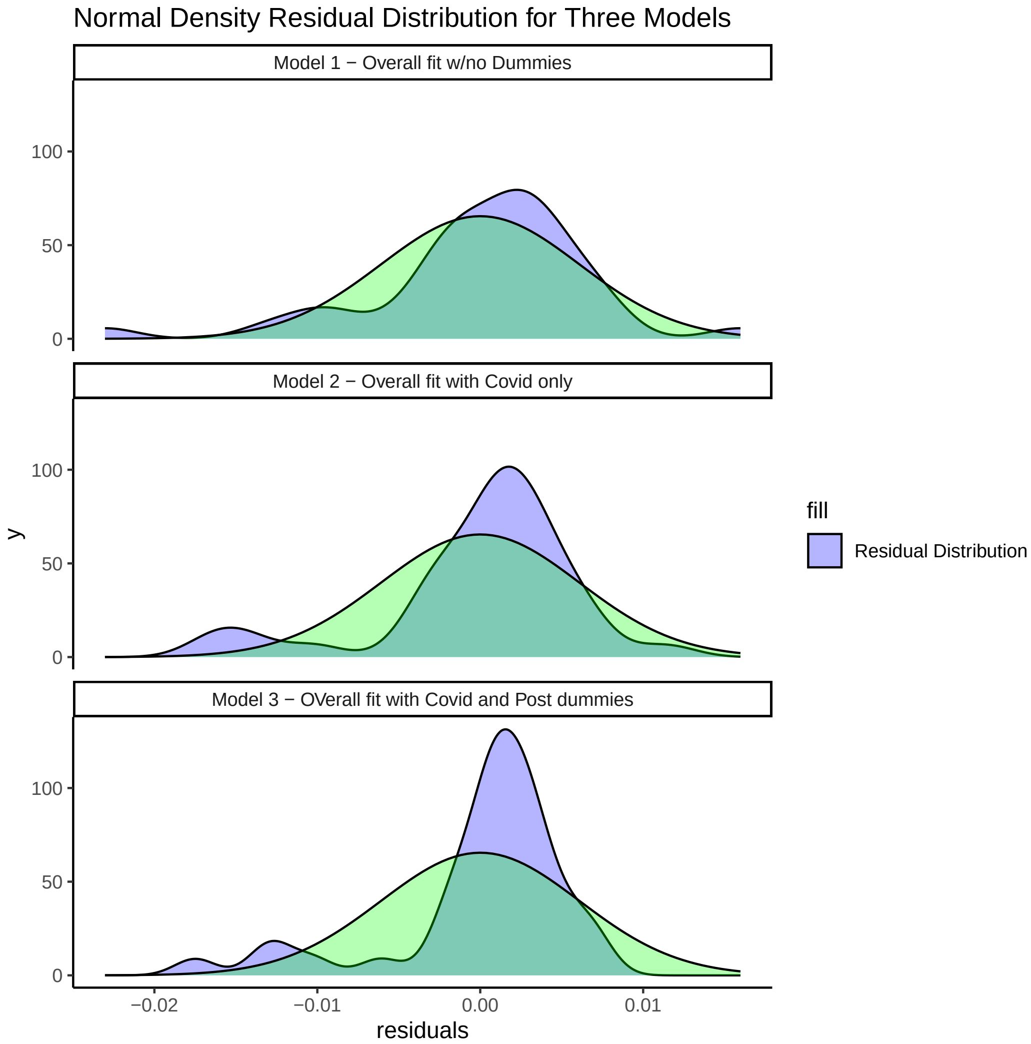
[5] I want to point out to your attention that during all my analysis, the variable I used (HTM, NII, ROA and Leverage) are calculated as an average across all banks. When however, I will talk in term of a single bank, I will make it clear and in this case the variable will just be the single observation for the given bank in a given period

```
## -0.0035608 -0.0009659 -0.0000455  0.0011066  0.0054335
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               1.194e-01  1.358e-02   8.796 9.81e-08 ***
## `I rates`                 1.469e+00  9.835e-02  14.940 3.30e-11 ***
## `Overall NII volatility`  1.373e-02  6.618e-03   2.074 0.053542 .
## `Overall ROA`            -4.077e+00  1.267e+00  -3.219 0.005039 **
## `Overall Leverage`       -3.647e-03  8.207e-04  -4.443 0.000356 ***
## `Inflation rate`         -1.452e-02  2.627e-01  -0.055 0.956560
## `OAS MBS spread`         -2.110e-05  9.061e-05  -0.233 0.818659
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.002331 on 17 degrees of freedom
## Multiple R-squared:  0.9566,Adjusted R-squared:  0.9412
## F-statistic: 62.38 on 6 and 17 DF,  p-value: 1.22e-10
##
## Call:
## lm(formula = `Overall HTM` ~ `I rates` + `Overall NII volatility` +
##     `Overall ROA` + `Overall Leverage` + `Inflation rate` + `OAS MBS spread` +
##     COVID_dummy, data = Covidonlyfit1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.016626 -0.002071  0.001251  0.003320  0.011404
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -5.221e-03  1.728e-02  -0.302   0.7648
## `I rates`                 9.510e-01  1.439e-01   6.610 3.60e-07 ***
## `Overall NII volatility` -1.058e-02  1.497e-02  -0.707   0.4855
## `Overall ROA`            -2.911e+00  1.904e+00  -1.529   0.1375
## `Overall Leverage`        4.474e-03  6.668e-04   6.711 2.77e-07 ***
## `Inflation rate`          7.723e-01  3.615e-01   2.136   0.0415 *
## `OAS MBS spread`         -8.513e-05  8.572e-05  -0.993   0.3292
## COVID_dummy              -1.202e-02  4.088e-03  -2.941   0.0065 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.006702 on 28 degrees of freedom
## Multiple R-squared:  0.8919,Adjusted R-squared:  0.8649
## F-statistic: 33.02 on 7 and 28 DF,  p-value: 6.7e-12
##
## Call:
## lm(formula = `Overall HTM` ~ `I rates` + `Overall NII volatility` +
##     `Overall ROA` + `Overall Leverage` + `Inflation rate` + `OAS MBS spread` +
##     COVID_dummy + post_dummy, data = overallfit1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.017494 -0.001073  0.001023  0.002775  0.007102
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)              4.802e-03  1.688e-02   0.284 0.778238
## `I rates`                9.738e-01  1.356e-01   7.181 1.01e-07 ***
## `Overall NII volatility` -6.153e-03  1.422e-02  -0.433 0.668621
## `Overall ROA`           -1.799e+00  1.862e+00  -0.967 0.342368
## `Overall Leverage`       3.480e-03  7.764e-04   4.482 0.000123 ***
## `Inflation rate`         4.511e-01  3.706e-01   1.217 0.234015
## `OAS MBS spread`        -1.255e-04  8.268e-05  -1.518 0.140527
## COVID_dummy             -5.297e-03  4.937e-03  -1.073 0.292782
## post_dummy               1.495e-02  6.891e-03   2.170 0.039013 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.006298 on 27 degrees of freedom
## Multiple R-squared:  0.908,Adjusted R-squared:  0.8807
## F-statistic: 33.31 on 8 and 27 DF,  p-value: 4.855e-12
```

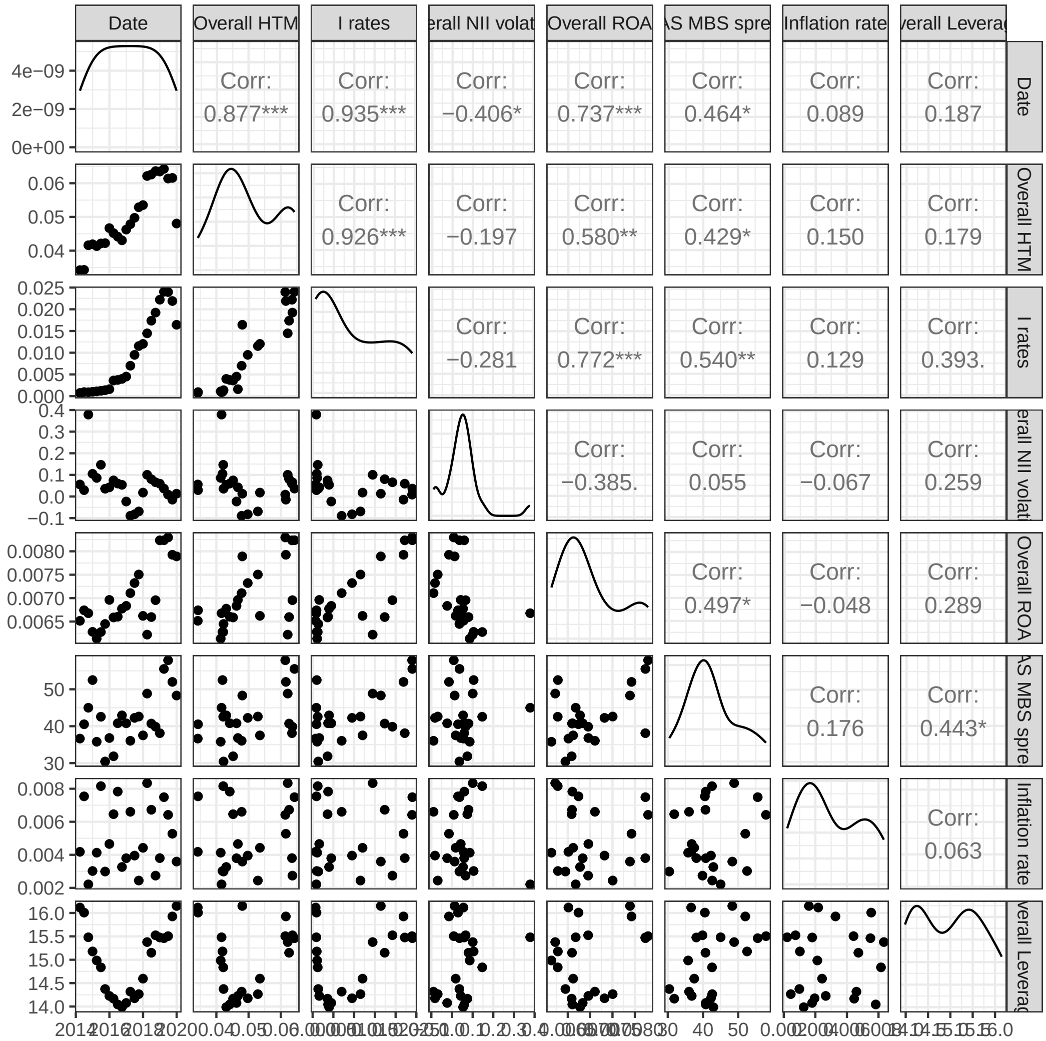
For these 3 tests (for a graphical representation please see refer to Appendix C), not only the Adjusted R-squared are highly significant in all the three cases but the models appear to satisfy the underlying assumptions of the linear regression as well. The variance of the error is homoscedastic as both the (check_heteroscedasticity) function and the Breusch-Pagan tests are significant, the errors are independent as they do not show any kind of patterns, the linearity of the data is good as the line in the graph is approximately flat, the VIF of the variables of the models are all below the value of 5 indicating little collinearity and the Bayesian posterior predictive check shows no systematic discrepancies between real and simulated data, signaling that the fitted model is compatible with the observed data. More interesting though, the OLS to be BLUE (Best Linear Unbiased Estimator) requires, in addition to all the tests I performed above, the normality of residuals. While in my analysis errors are normally distributed, this assumption is violated when I add the two dummies, indicating that, as I expected, the Covid-19 and post Covid market conditions have had a significant impact on the behavior of banks. Typically normality of residuals is violated because of certain observation in the sample size that strongly skew the distribution (outliers). As we can see from the figure C.2 and C.3 that you can find in the Appendix C, these influential observations are point 12 and 4, which indeed in my working file correspond to the beginning of the Covid pandemic (01-03-2020) and to the beginning of restrictive macroeconomic policies pursued by central banks to tame the mounting inflation (01-03-2022). Below I plot the non normality of residual for your view in which is clearly visible the violation of the normal distribution of errors.

Figure 3.4: Violation of normal distribution of errors assumption



Going back to R regression output, and beginning with the first regression, we can see at first glance that before Covid the reclassification from AFS to HTM was mainly influenced by Interest rates, ROA and Leverage, at a significance level of 99%. However, if we do not stop at the mere significance of the p-value but we dive deeper into the parameters of the output, I decided to drop ROA as explaining variable: this is because the standard error (which represents the average distance of the observed values from the regression line) is way too high, indicating that the parameter is not very much reliable. On the other hand, I decided to keep Interest rates and Leverage as significant variables during the pre-crisis period. Not only their significance is high but the standard error of the estimates is quite small. Moreover, if we pay close attention to the sign of the estimate and t-value of Leverage in the regression output, we can see that they are negative, indicating an indirect relationship. In layman terms this means that as leverage decrease the reclassification to HTM increases, which does not make much sense. In order to have a better idea of the relationships governing my regression model, I decided to plot here below a correlation matrix:

Figure 3.5: Correlation matrix - No mkt shocks



As we can see, and as we were expecting too given our first test above regarding the strong relationship between Interest rates and HTM during times of market normality, I rates have been the main driver in the reclassification from AFS to HTM during the pre-crisis period, with a correlation of 92.6%. Leverage on the other side presents only a weak correlation, at 17.9% indicating that during periods of market tranquility Leverage is not a determinant factor in the reclassification choice. More importantly though, is to look at its sign, which is positive. In my opinion this apparent contradiction can be due to the overfitting of the model. In the output table at page 28, I already showed that interest rates were quite significant in explaining the reasons behind the reclassification. However I decided to include all the other variables (NII, ROA,...) while performing this linear regression in order to get results comparable with the next two regressions (during Covid and post Covid). This came at a cost of overfitting, which created noise in the analysis which led to a change in signs.

By considering now the Covid and post Covid regressions output at page 36, we can see that ROA is not even significant anymore. Leverage increased in significance and above all, its sign is now positive, confirming our guess above regarding the true sign of the correlation. However what matter the most here is the gradual yet consistent shift in correlation intensity between Interest rates and Leverage as we move from pre-Covid period to Covid and post-Covid. As the table below clearly shows, Interest rates were undoubtedly significant prior to the pandemic but with the market shock brought-by the pandemic however, interest rates partly lost its explanatory role of why banks tend to reclassify more under HTM than AFS, in favor of Leverage.

Table 3.1: Shift in correlation significance

	Post Covid	Covid	Pre Covid
Interest rates	0.524 ***	0.478**	0.926***
Leverage	0.731***	0.484**	0.179

Economically speaking banks with a high Leverage ratio tend to reclassify more under HTM during periods of crisis in order to reduce volatility in their balance sheets. The pandemic caused significant market disruptions and increased levels of economic uncertainty, which in turn led to higher levels of credit risk. Banks with high levels of leverage were particularly vulnerable to losses from credit risk, as they had less capacity to absorb losses so that as a result banks faced the prospect of significant losses on their portfolios, which would inevitably reduce their capital ratios and potentially trigger regulatory restrictions on their activities. HTM reclassification therefore provided these banks a mean of self-protection, by detaching the transferred securities from the market-to-market pricing. Regarding my analysis, below you can see the effects of Leverage upon each single bank (for a full disclosure see the regressions in Appendix D):

Table 3.2: Leverage output for each bank

Both Dummies

	Estimate	Std.Er.	t-value	p-value
JPMorgan	0.0152	0.002738	5.55	6.96e-06***
BofA	0.0004326	0.000049	8.76	2.21e-09***
Citi	0.014158	0.002586	5.47	8.55e-06***
Citizens	-0.01183	0.002081	-5.68	4.86e-06***
Hsbc	-0.00783	0.002242	-3.49	1.63e-03**
MStanley	0.0169	0.004437	3.82	0.00069***
BNY	0.00654	0.012810	0.51	6.14e-01
Statestreet	0.01135	0.003731	3.04	5.19e-03**
Truist	0.02302	0.022780	1.01	3.21e-01
USB	-0.01698	0.008218	-2.06	4.86e-02*
WellsF	0.027111	0.008321	3.25	3.03e-03**

Covid Only

	Estimate	Std.Er.	t-value	p-value
JPMorgan	0.01416	0.002331	6.072	1.51e-06***
BofA	0.000412	0.00004	7.638	2.55e-08***
Citi	0.014502	0.00236	6.124	1.31e-06***
Citizens	-0.009517	0.00161	-5.885	2.49e-06***
Hsbc	-0.007329	0.00208	-3.518	1.50e-03**
MStanley	0.01781	0.00401	4.44	1.28e-04***
BNY	0.015433	0.01158	1.332	1.94e-01
Statestreet	0.009434	0.00447	2.107	4.42e-02*
Truist	0.011534	0.01790	0.644	5.25e-01
USB	-0.005161	0.00679	-0.76	4.54e-01
WellsF	0.029849	0.00733	4.068	3.50e-04***

No Dummies

	Estimate	Std.Er.	t-value	p-value
JPMorgan	-0.002244	1.32e-03	-1.69	1.08e-01
BofA	0.000046	4.13e-05	1.13	2.73e-01
Citi	-0.002178	2.30e-03	-0.94	3.56e-01
Citizens	-0.005856	2.20e-03	-2.63	1.64e-02*
Hsbc	-0.010785	4.06e-03	-2.65	1.66e-02*
MStanley	0.008289	6.02e-03	1.37	1.86e-01
BNY	0.024653	1.39e-02	1.77	9.32e-02
Statestreet	-0.023055	6.99e.03	-3.30	4.23e-03**
Truist	0.005510	2.27e-02	0.243	8.11e-01
USB	-0.042322	3.70e-02	-1.14	2.68e-01
WellsF	-0.004363	6.30e-03	-0.69	4.98e-01

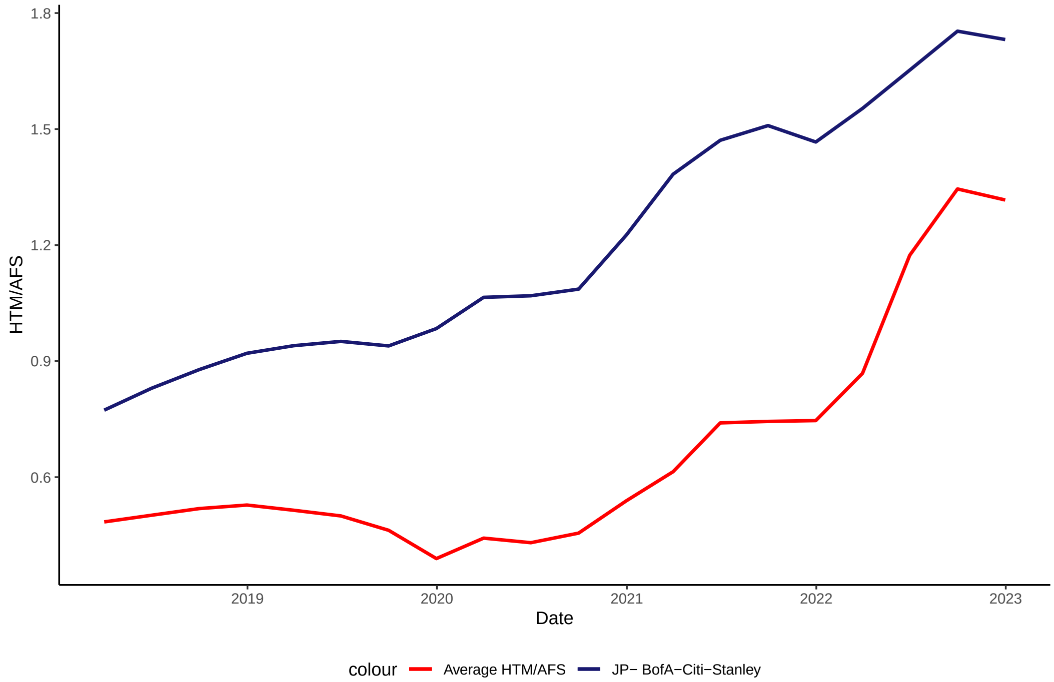
On the tale of what has been said above on Leverage significance on an aggregate basis, we still witness on a bank-wise level the shift in sign from mostly negative in the period prior to market stress to mostly positive during crisis. Furthermore, the negative sign of Leverage of Citizens and USBancorp throughout the three periods is manly addressed by their business models, which is slightly different compared to the business model of the great majority of banks included in the AA sample. Indeed Citizens and USBancorp are mortgage lenders whereas the other banks are mainly commercial banks, investments banks and asset managements banks. That being said, by looking at the parameters above JPMorgan, BofA, Citi and Morgan Stanley appears to be the banks for which Leverage is particularly significant. This is consistent with the general behavior of big financial conglomerates (these four banks altogether hold almost 45% of the total assets of U.S. banking system) for which, as the size increases, the leverage does too. Therefore, to observe the trend in changes in Leverage, on the table below I plotted the average change in Leverage as we move from no Covid period to Covid period and from Covid period to post Covid period.

Table 3.3: Average change in Leverage

	Post Covid - Covid	Covid - Before Covid
BofA	8.18%	23.70%
Citi	4.46%	30.05%
JPMorgan	5.86%	21.94%
MStanley	0.95%	5.98%
Average	8.30%	13.78%

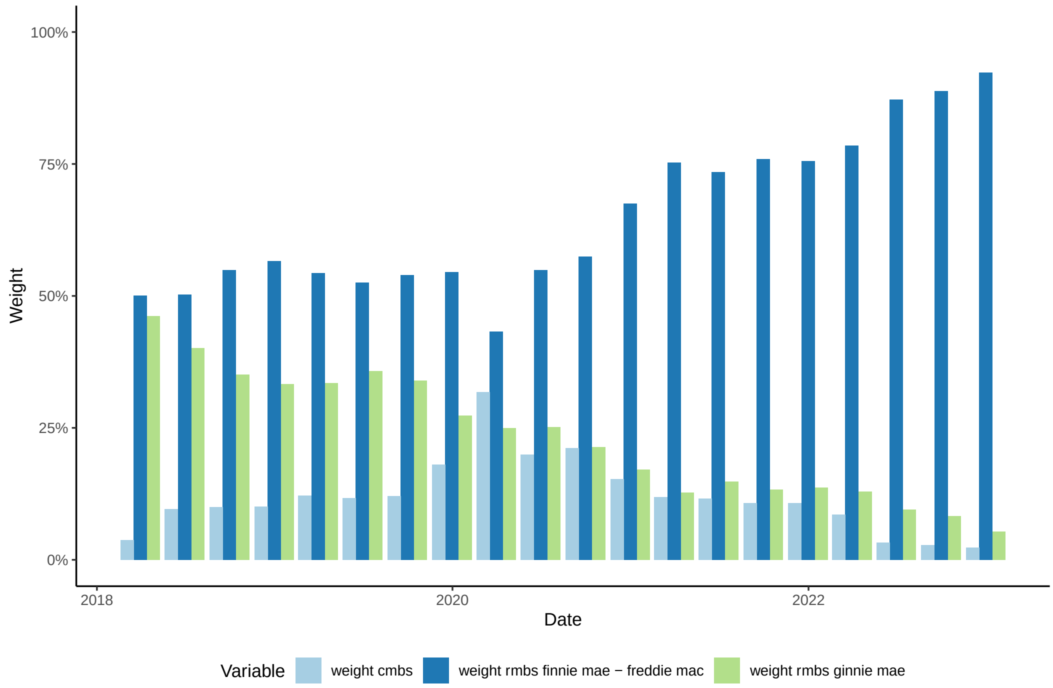
Apart from Morgan Stanley, as we were expecting for all the three other banks Leverage is way above the average Leverage and more importantly, these banks are also the banks that in relative terms, reduced the Leverage the most while moving from the pandemic to the post pandemic period. Therefore from these banks I expect a decisive increase in HTM reclassification:

Figure 3.6: HTM reclassification trend for JP- BofA-Citi-Stanley against the average for all banks



Indeed as we can clearly see from the plot above, HTM kept ramping up consistently during the pandemic period and after, reaching a peak at more than twofold the value at beginning of the pandemic. Now to have a better idea of what are the main security that are transferred the most from AFS to HTM, below I plot a graph showing the main trends in reclassification:

Figure 3.7: Asset classes reclassification trend for JP- BofA-Citi-Stanley



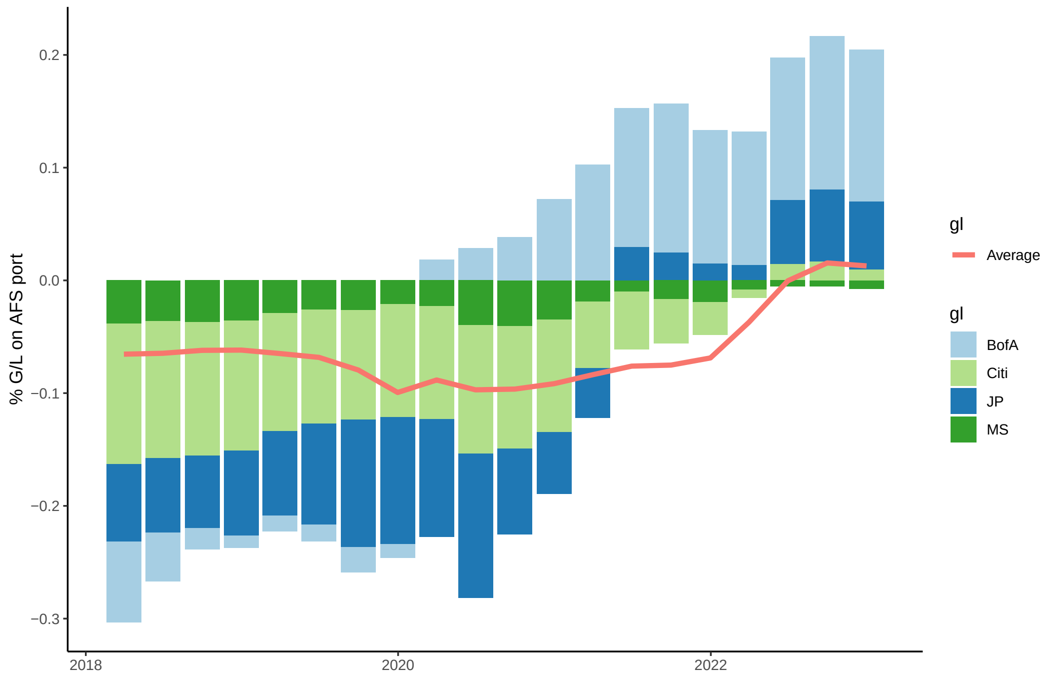
[6]The plot above has been created by by dividing each asset class HTM by AFS value. The idea behind the divison HTM/AFS is to capture any shift in reclassification from AFS to HTM. One may argue that by doing so I may end up considering new assets bought as HTM as well. Though this is a valid concern, it is not relevant in my analysis since reclassified as HTM or bought HTM both clearly show the willingness of the banks to keep those securities until maturity. Regarding the choice of the asset classes, namely: Residential mortgage backed securities issued by Ginni Mae, Freddie Mae and Finnie Mae and Commercial mortgage backed securities, I chose them as they represent the greatest,, if not the only one, categories of asset classes that banks reclassify from AFS to HTM. More in detail by looking at the graph we can see a neat preference for these banks to reclassify more Finnie Mae and Freddie Mac RMBS than Ginnie Mae RMBS and more RMBS compared to CMBS. Banks prefer to classify Fannie Mae and Freddie Mac MBS as HTM rather than Ginnie Mae based on the difference in the government guarantees. Ginni Mae are explicitly guaranteed by the U.S. government while Fannie Mae and Freddie Mac securities are implicitly guaranteed. This subtle but important distinction creates differences in the risk profiles and may encourage banks to protect their capital ratios from additional unwanted credit or liquidity risk. RMBS are preferred over CMBS

[6]To see how I calculated each variable, please refers to Appendix B

because notably RMBS give to the lender the right of foreclosure on the mortgage property thus allowing him to sell the property in order to recover funds toward satisfying the debt obligation. With CMBS however this is not possible. On top of that typically CMBS are less standardized under the contractual point of view, making it more complex to manage and hedge.

Finally, below I decided to plot the AFS unrealized gains/(losses) for BofA, Citi, JPMorgan and Morgan Stanley (normalized on the total size of the AFS portfolio to make results comparable across banks) against the average gains and losses for all the 11 banks analyzed. The idea behind this plot is to show the beneficial effects upon the 4 banks of the higher reclassification undertaken during the pandemic.

Figure 3.8: Impact of AFS unr g/l for JP- BofA-Citi-Stanley against the average for all banks



As we were expecting indeed, the four banks outperformed the average of the 11 banks all together. From 2020 onward, a higher reclassification allowed these 4 banks to get lesser exposure to the unrealized losses in their portfolios by isolating the reclassified securities from the volatility of interest rates, as the red line now appear to be a recipient containing all the bars. Particularly significant seems the results of BofA and JPMorgan, which clearly stands out against Citi and M.Stanley.

Findings summary: While during periods of market calmness changes in Interest rates are the main driver in the choice of banks to reclassify more or less (depending on the direction of the change) HTM over AFS, during periods of market stress Interest rates, while still remaining relevant, are not the only factor that comes into play. Among NII Volatility, Leverage, ROA, OAS on MBS and Inflation rate, Leverage is the only variable that seems to play an important role in explaining the reclassification choice during and after the pandemic, as the correlation analysis demonstrate. At a bank-wise level, at a significance level of p-value higher than 99%, the banks more affected by Leverage during periods of economic downturn turned out to be JPMorgan, BofA, Citi and Morgan Stanley. This is somehow consistent with the general behavior of big financial conglomerates for which, as the size increases, the leverage does too. Therefore from these banks I expected a higher than average reclassification of securities and indeed the data show a more consistent reclassification throughout the whole crisis period. In terms of the actual securities that have been reclassified from AFS to HTM during Covid and post Covid crisis, RMBS seemed to be the preferred asset class, and more in detail Finnie Mae and Freddie Mac RMBS were reclassified more under HTM than AFS than Ginnie Mae RMBS, and RMBS were reclassified more under HTM than CMBS. Differences in government backing guarantee make Finnie Mae and Freddie Mac a stronger candidate for reclassification than Ginnie Mae. Differences in contractual complexities and investors protection mechanisms make RMBS more appealing for reclassification over CMBS. Finally regarding the effects of the reclassification, from the last plot we proved the actual benefits of the higher than average reclassification from AFS to HTM. Particularly significant appears to be the results for JPMorgan and BofA which not only outperformed the average but also the other two peers, indicating a more effective risk management strategy.

Chapter 4

Effects of the reclassification upon the Volatility of the Regulatory Capital

4.1 Assumptions

As discussed in the introductory section, the main difference between AFS and HTM is that for the former, all the unrealized gain and losses are included in the regulatory capital, thus making it way more volatile than it would be under HTM regime, as all the unrealized gain and losses are excluded from it. As a result I assume and expect to see that following a reclassification from AFS to HTM, the volatility of the regulatory capital of banks will decrease accordingly.

4.2 Methodological Approach

In order to study the effects that the reclassification from AFS to HTM has on the volatility of banks, I used the linear regression model outlined below:

$$\hat{Y} = \alpha_0 + \beta_1(HTM) + \lambda_i + +\varepsilon i$$

where the dependent variable is the Volatility, represented by the Volatility[1] of the Tier 2 capital (as the AFS unrealized gain and losses flows into this part of the Regulatory capital). HTM is represented by the an average of the Held to Maturity securities held by BofA-Citi-JP-MS, which are the banks that reclassified the most, scaled by total assets and λ represents fixed-effect banking variables, represented by:

- Deposits: to account for bank's size;

[1]See Appendix B to see how I calculated the variables

- Liquidity Coverage Ratio: to account for bank's liquidity;
- ROE: to account for bank's profitability and
- Loan Growth and Loan risk: to account for the bank's business model.

Also, regarding the time frame of my analysis, while in the third chapter I performed my analysis in three different time-frames (prior to Covid - during Covid - after Covid), here I will focus my attention only on the period where the biggest reduction in Volatility happened. Banking is one of the most complex and regulated industries. Countless stakeholder hold interests in the banking sector and as a result the regulatory capital of banks is extremely volatile. As a result, the regulatory capital of banks can be affected by a variety of factors, including changes in market conditions, economic downturns, changes in government policies, and shifts in public sentiment towards the banking industry. Therefore in an attempt to reduce unwanted noise in the trends and to reduce the possible impact of FED regulations, I decided to focus my attention only on the time period where the biggest reduction in Volatility happened.Therefore for JPMorgan the dummy will be placed for the period that spans from the third quarter to the fourth quarter 2020, for BofA from the fourth quarter 2020 to first quarter 2021 and for Morgan Stanley from the fourth quarter 2021 to the second quarter 2022. Conversely, for Citi I won't analyze the period concerning the biggest reduction in Volatility, as there is not any, but instead I will focus my attention on the period corresponding to the biggest increase in Volatility, from the first quarter 2022 to the end of the fourth quarter 2022[2].

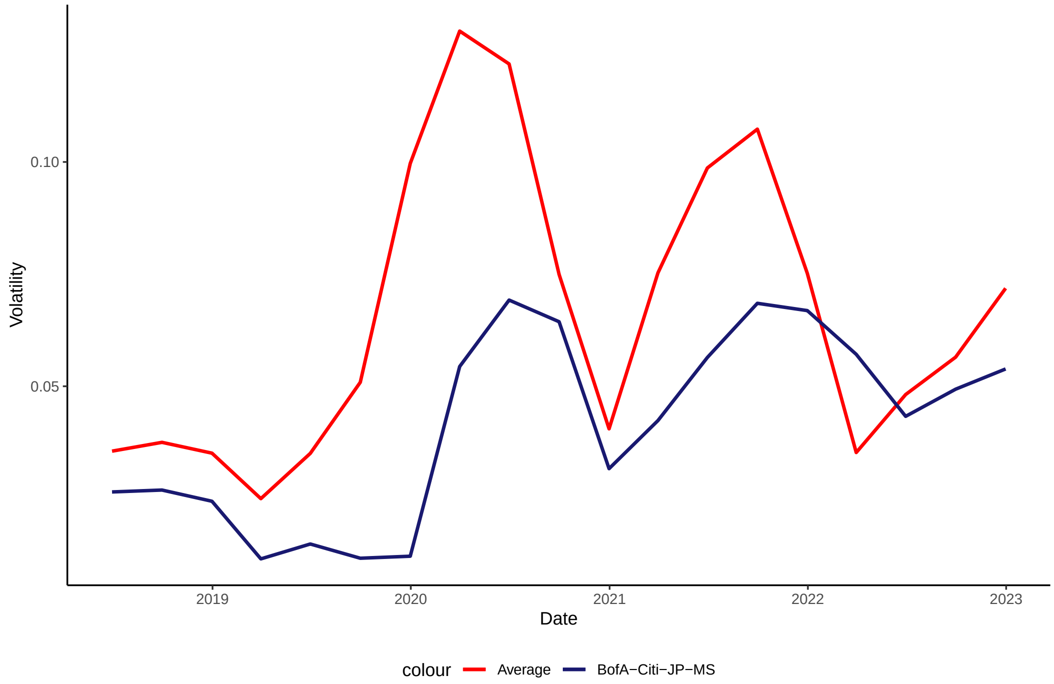
4.3 Hypothesis and Findings

H2: *An increase in HTM reclassification reduces the Volatility of the Regulatory Capital of banks*

The figure 3.6 shows that Bank of America, Citigroup, JPMorgan and Morgan Stanley were the banks that reclassified under HTM the most. As I am expecting that a higher reclassification leads to a lower volatility of the regulatory capital, to have a clear view of the Volatility trend across banks, I thought to plot the Volatility of the Tier 2 capital from 2018 to 2022.

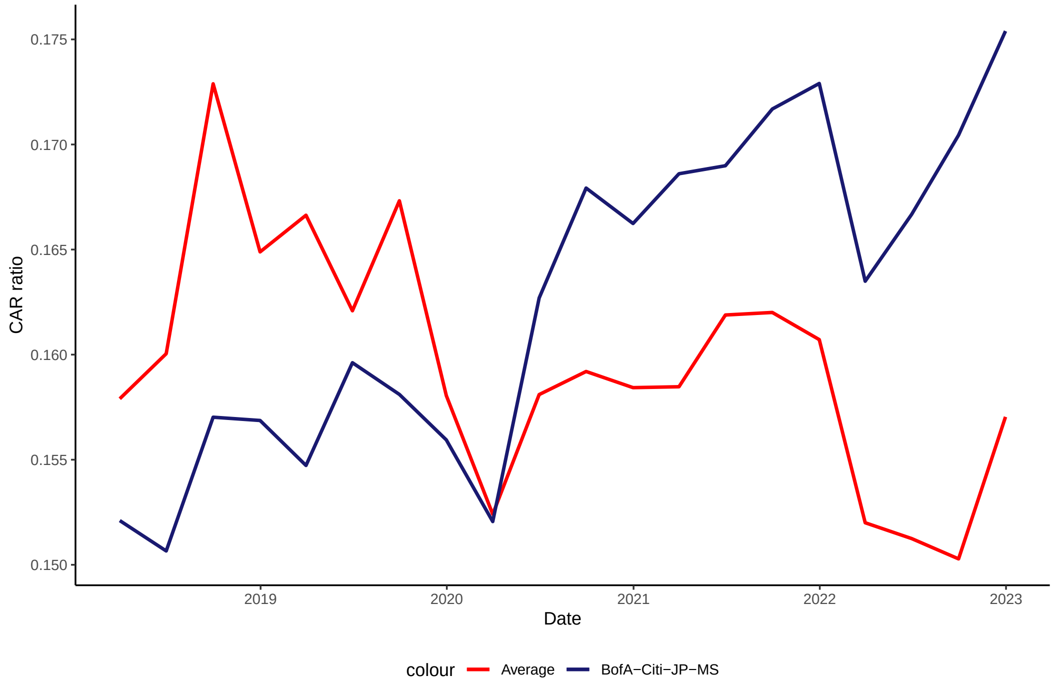
[2]Look at the plots in Appendix E

Figure 4.1: Tier2 Volatility across banks



From the plot it is possible to see that on average these four banks were able to achieve a lower volatility of the regulatory capital. I then did a step further and with the data I had already gathered I calculated the Capital Adequacy Ratio, which is a ratio closely monitored by regulators since a higher CAR ratio means that a bank is more stable and efficient. Therefore I plotted a graph to see if indeed the higher HTM reclassification from BofA-Citi-JP-MS make them appear more stable and efficient compared to the average of the eleven banks:

Figure 4.2: CAR ratio



As we can see from the graph, exactly from 2020 we witness an inversion in the trend with the red line crossing from above the blue line representing the average of the eleven banks. From figure 3.6 though, we know that exactly at the beginning of 2020 BofA-Citi-JP-MS underwent higher than average HTM reclassification. Therefore if we combine these two graphs it is plausible to expect that the higher HTM reclassification made these bank look more stable and efficient as the higher than average CAR ratio would suggest. Now that I have a broad picture of the Volatility and the CAR ratio, I dive deeper into each one of the four banks to study if the HTM reclassification is the real reason behind the lower Volatility and higher CAR.

4.3.1 JP Morgan

By running the regression model outlined above[3], although the test statistics are highly significant, we can see that from the third to the fourth quarter of 2020, HTM reclassification did not play the relevant role in explaining the reduction in volatility that we were expecting to see. Instead other variables seem to play a more determinant role, such as Deposit and Loan risk at a significance level of 95%. In order to see the true relationship between these two variables I then performed a sub-regression (Deposit-Loan risk) and I have found that indeed these two variables have a strong bond with an R-squared at 86% and a correlation of -0.913***. Furthermore I then performed a correlation analysis between the interaction term defined

[3]For the regression output relating to this chapter, please see Appendix E.

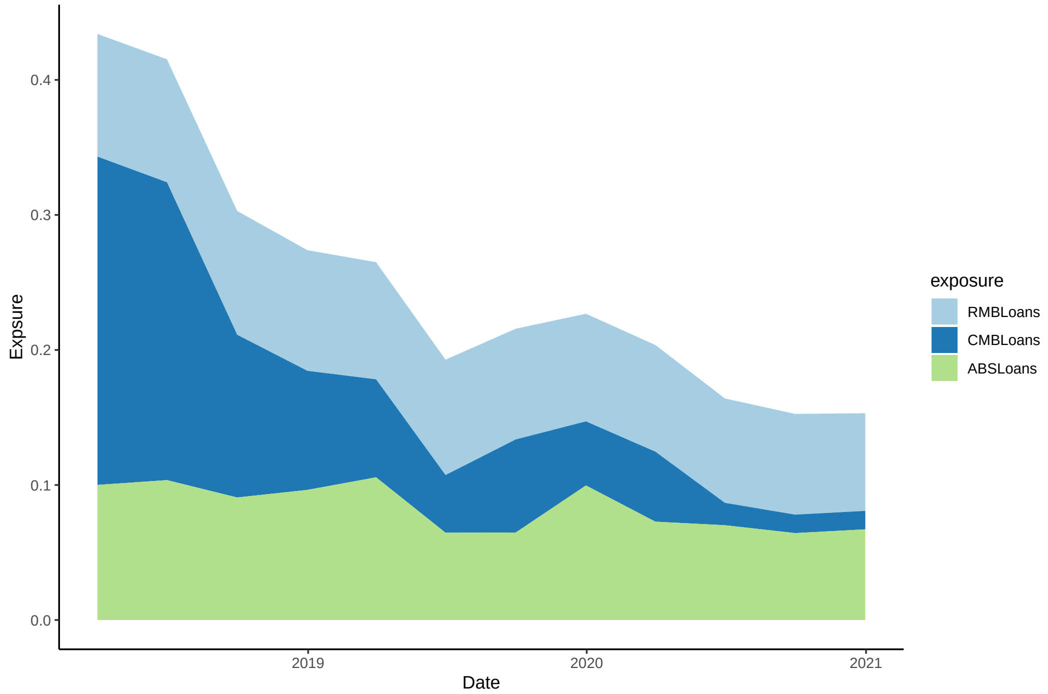
as (Deposit*Loan risk) and Volatility to see if indeed an increase in deposit and a reduction in loan risk translates into a reduction of the volatility of the regulatory capital and I found that this correlation is strong and positive at a confidence level of 99% (0.705**). This is particularly insightful: as the deposits increase, the riskiness of the loans decreases, as the bank has now more money to reinvest back in its operations. This translates into a lower RWA weighting thus reducing the Volatility of the regulatory capital. I then studied the composition of the loan portfolio of JPMorgan and its evolution in time and I found that indeed from 2018 to the end of 2022, JPM significantly reduced its exposure towards its riskier loans by progressively divesting:

- The riskier Residential Mortgage backed loans represented by BHCs codes (BHCKS417, BHCKS441, BHCKS443, BHCKS178);
- High volatile commercial real estates (BHCKS182, BHCKS447);
- Auto loans, student loans, personal loans, and equipment leases (BHCKS462, BHCKS463);
- Non Performing Loans (BHCKS454)[4].

For these balance sheet entries, the RWA weighting was 100 – 150%. Therefore a progressive reduction in these exposures allowed the bank to get some regulatory relief thus lowering the volatility of its regulatory capital. Lastly I thought it was interesting to study the composition of the deposit of JPM and I have found a progressive relevance of non interest paying deposits, which is good for a bank, as the bank is getting money to invest in its operations without having to bear the interest costs.

[4]To have a look at the tables, please refers to Appendix E

Figure 4.3: JPMorgan Loan Exposure



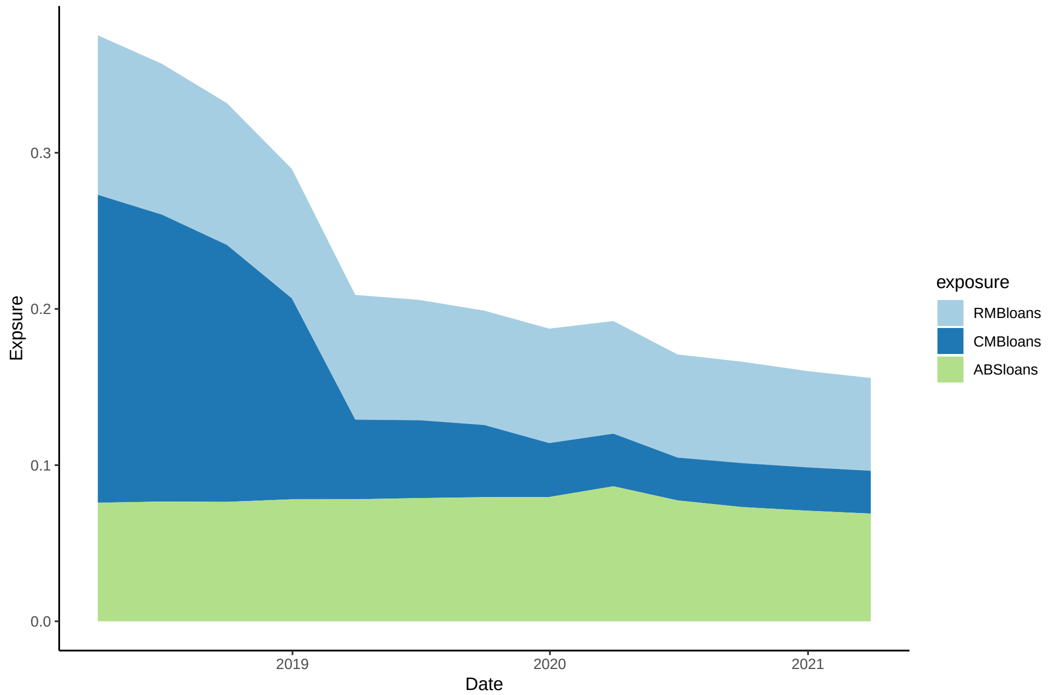
4.3.2 Bank of America

For BofA, we can see from the regression output that Volatility has been influenced by 3 mains variables: HTM, Deposit and Loan risk. HTM played a pivotal role in the reduction of Volatility. The parameter is highly significant at a 99% confidence level and is inversely related to the dependent variable, correctly indicating that as HTM reclassification increases, the Volatility decreases. I then ran the correlation matrix to spot for the real relationship between HTM-Volatility and I found a correlation coefficient of -0.97 indicating a deep bond between the two variables. Moreover, particularly interesting is the relationship between Deposits and Loan risk. Between these 2 variables the correlation is significant at a 95% confidence level at -0.559*, indicating again that as deposit increases, the riskiness of the loans decreases, as the bank has now more money to reinvest back in its operations. This allow the bank to allocate its capital to less risky loans. Also it is particularly insightful to look at the deposit composition as well. As we can see from the graph from 2018 to the first quarter 2021 the non interest paying deposits increases compared to the interest paying ones, allowing the bank to reinvest this money without having to pay for them. By studying the relationship between Volatility, Deposit and Loan risk I found that this relationships is significant at a 95% level, at -0.566^*. Continuing our discussion above regarding the relationship deposit and loan risk, BofA decreased the riskiness of its loans from 2018 to 2022 by progressively divesting:

- The riskier Residential Mortgage backed loans represented by BHCs codes (BHCKS443, BHCKS441, BHCKS415, BHCKS417, BHCKS416);
- High volatile commercial real estates (BHCKS447);
- Auto loans, student loans, personal loans, and equipment leases (BHCKS437, BHCKS460, BHCKS462, BHCKS463).

For these balance sheet entries, the RWA weighting was 100 – 150%. Therefore a progressive reduction in these exposures allowed the bank to get some regulatory relief thus lowering the volatility of its regulatory capital.

Figure 4.4: BofA Loan Exposure



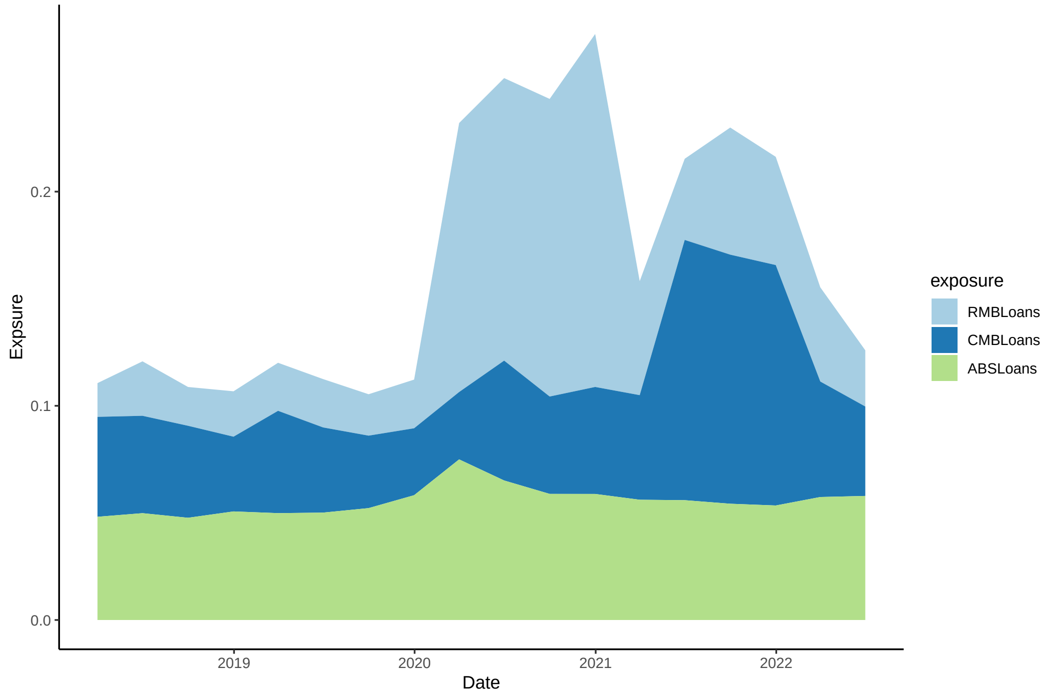
4.3.3 Morgan Stanley

For Morgan Stanley as well, the model outlined above worked out well. The test statistics are highly relevant, with a Multiple R-squared at 90% and with the parameters HTM, Deposits and Loan risk highly significant. Particularly relevant appears to be the HTM variable, which is significant at the 99% confidence level. Moreover, it is negatively related to the dependent variable, correctly indicating that as HTM reclassification increases, the Volatility decreases. Deposits and Loan risk are relevant as well and, as I already did for the three banks above, I performed the correlation analysis between Deposits and Loan risk first, and then I multiply these 2 in order to get the interaction term with which I run a correlation analysis with the Volatility to see if an increase in deposits and the subsequent reduction in loan risk really cause the Volatility to decrease. As a result, I got that the correlation between Deposits and Loan risk is a strong negative one, at -0.722*** and then by performing the correlation analysis between Volatility and interaction term I found a negative and strong significance, at -0.787 indicating a strong and negative tie. I then studied the composition of the loan portfolio of Morgan Stanley and its evolution in time and I found that indeed from 2018 to the second quarter, 2022 , MS significantly reduced its exposure towards its riskier loans by progressively divesting:

- Residential mortgage loans (BHCKS416, BHCKS417, BHCKS443) for which the 50%-100% weightings apply;
- Non performing loans (BHCKS429), with a 150% weighting;
- Auto loans, student loans, personal loans, and equipment leases (BHCKS434, BHCKS436, BHCKS460, BHCKS461, BHCKS462) with weightings ranging from 20%,50% and 100%.

As a result of the progressive reduction in these exposures the bank was able to get some regulatory relief thus lowering the volatility of its regulatory capital.

Figure 4.5: Morgan Stanley Loan Exposure



4.3.4 Citi

Regarding Citi, as it is possible to see from the graph of the volatility in Appendix E, it appears that the bank HTM reclassification did not contributed to reducing the Volatility of the regulatory capital, or if it did then there must have been some other event that outweighed the benefits of the HTM reclassification. I then began by performing the linear regression model proposed above but did not worked out well. Even though the statistics of the model indicated a good fit, with a multiple R-squared at 77% and with all the underlying assumption of the linear regression respected, the output did not make sense under the economics point of view. More in detail, the HTM variable was relevant at a 95% level but it was strongly and positively correlated with the Volatility, as if an increase in HTM increased the Volatility of the regulatory capital, which does not make sense at all also because the Volatility from 2018 to 2021 increased constantly. Therefore I thought that this extra volatility could be given by the risk implied within the AFS securities that Citi decided not to reclassify. I performed the analysis by focusing on the part of the graph where the Volatility rocketed up and my guesses were confirmed. AFS risk is highly relevant at a 99% confidence level. The model overall was relevant as well, with a multiple R-squared of 93% and all the underlying assumptions (mainly normality, heteroscedasticity, Breusch-Pagan test) were all significant. I then moved on studying the correlation among variables, specifically between the Volatility and

AFS risk and I found quite a strong bond between these two variables, at 0.926*** indicating almost a perfect correlation. Following logically I then thought that if AFS risk is relevant then AFS unrealized gain and losses must be relevant as well as they flow directly into the Tier 2 capital making it more volatile. Therefore I run a sub-regression just among Volatility, AFS risk – AFS unr g/l and I found that the model is significant with a multiple R-squared at 90% . Lastly to see if the AFS risk and AFS unr g/l together influenced the Volatility, I ran a correlation analysis between Volatility and the interaction term (AFS risk*AFS unr g/l) and I found a strong positive relationship significant at a 99% confidence level, indicating that AFS risk and AFS unr g/l strongly influenced the volatility of Citi regulatory capital. Therefore, compared to the other three banks of the sample, Citi seemed to have been the bank that decided to cover the lesser from the AFS unrealized gain and losses exposure. However the decision not to cover this risk is in some way respectable. We know that even if HTM reclassification provides regulatory capital relief, it also greatly reduces the liquidity of the portfolio, thus making it more difficult for the bank to exploit favorable market cycles.

Findings summary: As we can see from my analysis above, although significant for two out of the four banks analyzed, HTM reclassification does not seems to be the only strategy banks used while trying to reduce the volatility of their regulatory capital. An inflows of capital in the form of higher deposits has allowed banks to gradually reduce the riskiness of their loan exposures by specifically divesting the loans to which a high RWAs weighting apply. That being said, the banks upon which the HTM reclassification appears to have had significant effects are BofA and Morgan Stanley. For these banks not only HTM variable was highly significant at a 99% confidence level, but the relationship with the dependent variable was negative, correctly indicating that as HTM reclassification increases, the Volatility of the regulatory capital decreases as the unrealized gain and losses are not flowing on the regulatory capital anymore. In addition these two banks implemented a second strategy to reduce the Volatility of their regulatory capital by combining the Deposit and Loan risk: as the deposits increase, the riskiness of the loans decreases, as banks have now more money to reinvest back in its operations, thus allowing banks to allocate their capital to less risky loans. These two variables were highly significant, for BofA at a 99% and 95% confidence level while for MS at 100% and 95% confidence level. However this strategy appear to be far more significant for MS than BofA as the correlation between the interaction term and Volatility shows (-0.78 for MS and -0.57 for BofA). For JPMorgan the HTM reclassification strategy did not turned out to be significant, as the linear regression output shows. In contrast though JP used even more significantly than the two banks just mentioned above the increased Deposits to reduce the riskiness of its exposures. Deposits and Loan risk has an almost perfect negative correlation, at -0.913 significant at 100% confidence level and the correlation between Volatility and the interaction term is significant at a 99% confidence level at 0.75, indicating that for JP this strategy was particularly determinant in reducing the Volatility of its regulatory capital. The plots of the volatility in Appendix E shows that for BofA, JP and MS Volatility is decreasing, whereas for Citi it remained stable for a while just to blow-up toward the end of the observation period. Therefore it is plausible to think that for Citi the benefits of the HTM reclassification were outweighted by the risk implied within the AFS securities that Citi decided not to reclassify. After having performed the due analysis, I have that indeed the huge increase in Volatility from the first quarter 2022 to the fourth quarter 2022 is mainly attributable to the AFS risk. More in detail, I run a correlation test between Volatility, AFS risk and AFS unrealized gain and losses and I have found that the fluctuations of the AFS unr g/l are the main reasons behind the unwanted increase in Volatility. However the decision not to cover this risk is in some way respectable. We know that even if HTM reclassification provides regulatory capital relief, it also greatly reduces the liquidity of the portfolio, thus making it more difficult for the bank to exploit favorable market cycles.

Chapter 5

Effects of the reclassification upon the market Liquidity

5.1 What Liquidity is and how it is measured

According to the definition provided by Abdourahmane Sarr (2002), market participants perceive a market to be liquid if they can sell large amount of an assets without adversely affecting its price. Liquid financial markets are thus characterized by having small transaction costs; easy trading and timely settlement; and large trades having only a limited impact on the market price. In order to asses that liquidity, Bervas (2008) outlined three main measures: market depth, bid-ask spread and market resilience. Market depth refers to the ability of the market to sustain a substantially larger order without having an impact on the security's market price, bid-ask spread is the difference between the highest price a buyer will offer and the lowest price a seller will accept. Typically, an asset with a narrow bid-ask spread will have high demand. By contrast, assets with a wide bid-ask spread may have a low volume of demand, therefore influencing wider discrepancies in its price. Market resilience refers to how fast market prices return to their normal values after that an over sized transaction took place, or in other words it measures how well a market is able to absorb significant price fluctuations.

5.2 Assumptions

As the HTM securities cannot be sold as freely as they would under AFS unless the tainting of the portfolio, I assume and expect this locking-up of these securities to cause a significant reduction of liquidity in the markets. As a result I also expect the trading revenues of banks to decrease substantially, for trading revenues can be seen as a compensation for banks to provide the market with liquidity.

5.3 Data sample size and Methodological Approach

In the figure 3.7 we have seen that the most preferred asset classes for HTM reclassification are Finnie-Mae and Freddie-Mac while Ginnie-Mae is the less preferred. Therefore in order to study the liquidity of these particular three asset classes I downloaded from SIFMA and FINRA[1] their daily trading prices, volumes of trades and number of trades. As there are various markets (CMO, MBS and TBA), I decided to focus my attention on the TBA (To Be Announced) market as it the most active market when it comes to RMBS trading. Once I selected the market I had to decide the segment (Agency Pass-Through Single Family 15 years, Agency Pass-Through Single Family 30 years and Agency Pass-Through Arms/Hybrids) and I decided to focus on the single family 30 years segment as it better reflect the true long maturity nature of the underlying residential mortgages. Then, once I knew the direction to follow I gathered the daily trading data and I calculated a monthly average[2]. From this data I began calculating liquidity indices, which consist of :

- Amihud Illiquidity Factor;[3]
- Market Depth;
- Market Resilience;
- Interdealer trades;
- Numbers of trades and Trading Volume.

The Amihud factor is one of the most used indicator to assess the liquidity of a financial asset. It usefulness derives from its capacity to capture the price impact of a trade while taking its size into account. Interdealer trades are extremely meaningful too, as a greater percentage of interdealer trades is indicative of greater reluctance to provide market liquidity on the part of dealer because it indicates that dealers, rather than absorbing the customer order imbalances on their own balance sheets, are spreading order imbalances across the dealer network.

To study the effects that the higher HTM reclassification has had on the liquidity of markets, I set-up a linear regression model similar to the one used in chapter 4 but with different control variables:

$$\hat{Y} = \alpha_0 + \beta_1(HTM) + \lambda_i + +\varepsilon i$$

[1]Please see the Appendix for the websites.
[2]To have an idea of what the data look like, please refers to Appedix F
[3]To see how I calculated each variable, please refer to Appendix B.

where the dependent variable is either the Trading Volume or the Number of Trades relating exclusively to Finnie-Mae and Freddie-Mac RMBS. HTM is represented by the average of the Held to Maturity securities held by BofA-Citi-JP-MS, scaled by total assets and λ represents control variables related to the economic and financial environment:

- U.S. Term spread: being the term spread the difference between short and long term government bond, if it positive then this spread can be seen as a sort of premium that can be earned by locking-in funds for longer maturities. This interpretation is quite close to the concept of HTM reclassification as the securities are locked-up for the long term;
- S&P 500 return: by including the S&P monthly return in my analysis, I factored in the performance of the US economy;
- VIX and Option-Adjusted-Spread (OAS): I decided to include these two measures of market volatility for VIX allow me to count-in in the model the perceived riskiness of the overall US economy, while the OAS spread allowed me to focus exclusively on the MBS market volatility. By including them both I can achieve a complete picture of the perceived volatility in the markets.

Regarding the time-frame, I'll resume the time tranches I applied in chapter four, by focusing on Covid (2018-03-30 to 2021-12-31) and Post-Covid period (2022-03-01 to 2022-12-31).

Moreover, to test the impact that the higher Finnie-Mae and Freddie-Mac HTM reclassification has had on the trading revenues of BofA-Citi-JP-MS, I set up this regression model:

$$\hat{Y} = \alpha_0 + \beta_1(UMBS) + \lambda_i + +\varepsilon i$$

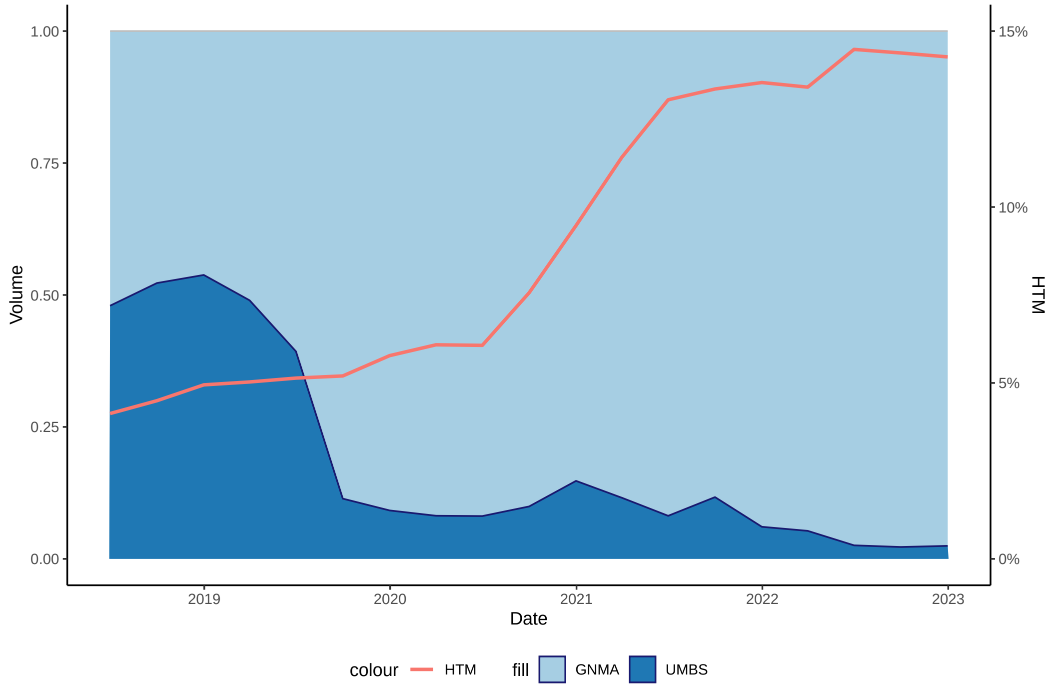
where the dependent variable is represented by the Trading Revenues, UMBS stands for Finnie-Mae and Freddie-Mac while λ is comprehensive of the same control variable as above.

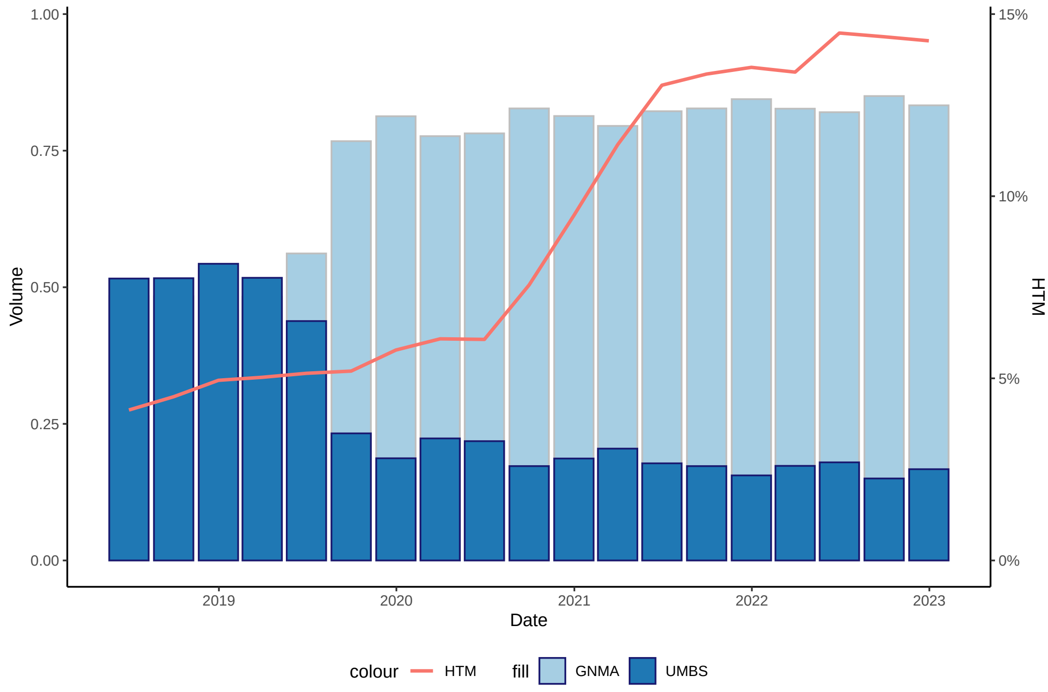
5.4 Hypothesis and Findings

H3: *A higher HTM reclassification reduces the Liquidity of the markets*

As we already know, once a security is reclassified to HTM it is not possible then to switch back to AFS or HFT unless the tainting of the whole portfolio, which would be priced marked to market instantly with the subsequent inclusion in the regulatory capital of all those unrealized gain and losses. Therefore the locking up of these security adversely impact the liquidity of markets, as the securities cannot be freely traded anymore. As far as the data I gathered concern, from 2018 to 2022 the HTM over total assets grew from 2% to almost 10% for the four banks BofA-Citi-JP-MS, taking away from markets roughly \$5bn of liquidity in 2018 to almost \$35bn at the end of 2022. Below you can see the two plots showing the volume of the trades concerning the Freddie-Mac and Fannie-Mae over time and the number of trades:

Figure 5.1: Trading Volumes and Number of trades





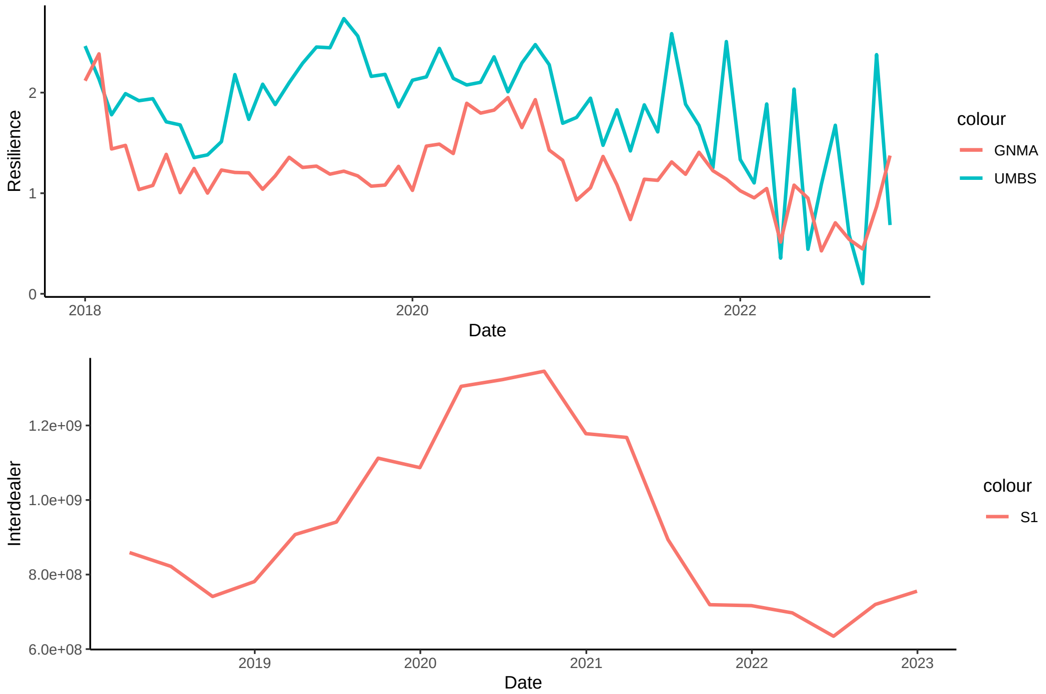
As you can see from the plots an increase in HTM reclassification by the four major banks reduces both the number of trades and the volume of the transactions relative to Finnie-Mae and Freddie-Mac RMBS compared to Ginni-Mae which instead remains liquid. By firstly performing the linear regressions outlined above[4] against the Trading Volumes, we can see that the test statistics are quite high, with a multiple R-squared at 82%, the underlying assumptions of the model are respected, namely the normal distribution of the residuals, heteroscedasticity, multicollinearity and homogeneity of variance. More importantly however, is the significance of the parameters, or in this case, of the parameter HTM which is highly significant at 100% confidence level and negatively correlated with Trading Volume, correctly indicating that as HTM reclassification increases, the volume traded decreases. Furthermore, by performing a correlation analysis among variables, I found that between the dependent variable and HTM reclassification exists a strong negative correlation significant at 99% confidence level, at -0.651**. Moreover as the graph already suggests, the dummies are not significant as the biggest fall in trading activities happened at the beginning of 2020. By extending my analysis until the end of 2022, the model produces still highly significant results, with a multiple R-squared at 81% and HTM still significant at 100% confidence level. The correlation between the dependent variable and HTM got even stronger, at -0.807***. In terms of number of trades instead, intuitively we should get almost the same significance and results we got for trading volume above, as the two variables are strictly correlated, and indeed I found that the reclassification carried out by BofA-Citi-JP-MS significantly impacted the number of trades for Finnie-Mae and Freddie-Mac as well. Recalling now the plot illustrated in the figure 3.6, showing that BofA-Citi-JP-MS reclassified under HTM much more than the other banks (Citizens,HSBC...), I then tried to back-test the results of the regression above by performing the same regressions using the average HTM scaled by total assets for Citizens,HSBC and the other remaining banks and indeed I have found that the amount of the reclassified securities by these banks did not have a significant impact on volume traded in the market as well as upon the actual number of trades.

As a consequence this decrease in volume and number of trades significantly impacted the liquidity of market as a whole.

[4]For the regression output please refer to Appendix F.

Figure 5.2: Amihud factor - Mkt Depth

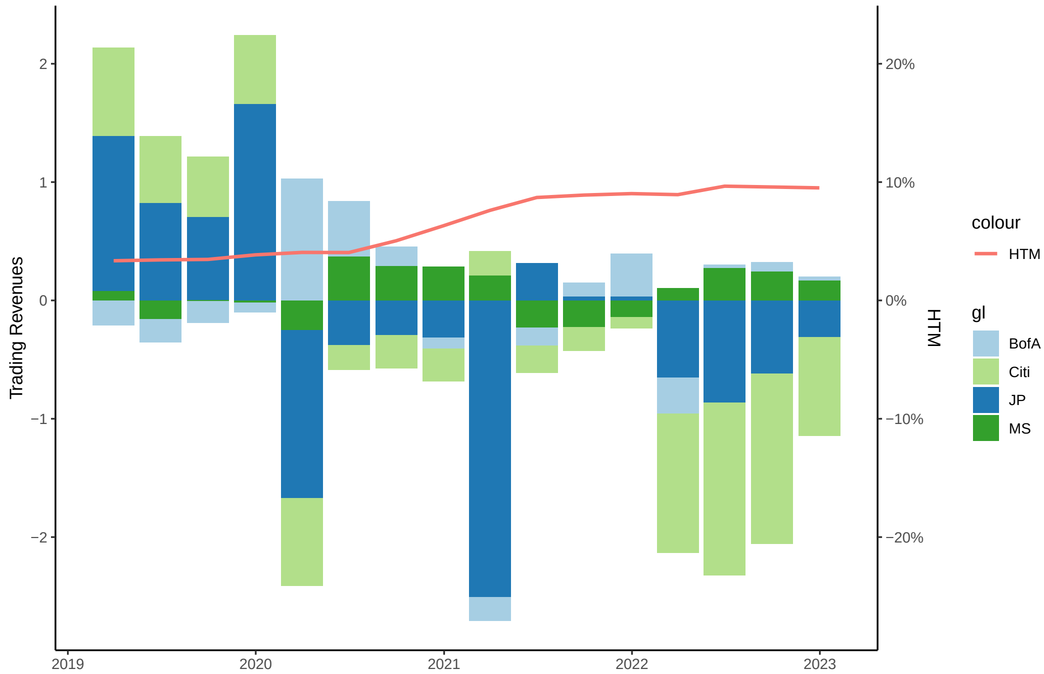
Figure 5.3: Resilience - Interdealer Trades



The first parameter I analyzed is the Amihud factor, as it is one of the most widely used indexes when it comes to measuring illiquidity and it is calculated by dividing the absolute value of the daily price return by the average dollar volume of the daily trading session. As we can see from the plot above, the line representing the illiquidity relative to Finnie-Mae and Freddie-Mac peaked in 2019 when banks began to reclassify massively to HTM (see figure 3.6), to remain always all the way above the line representing Ginni-Mae. By looking at the figure 5.1, we can see that in 2023 the volume of Finnie-Mae and Freddie-Mac traded was strikingly low, contributing to the ramping up of the Amihud factor once again. By focusing now on the market depth, I calculated it by taking the difference between the average top five prices and the average of the bottom five prices. From the plot it is possible to see that for Ginnie-Mae this difference is wider, indicating that the market for these kind of securities offers a wide range of prices thus satisfying a higher number of investor price requests. For Finnie-Mae and Freddie-Mac however the market is not very deep and this is concerning because investors are not able to convert quickly in cash their position if the price they are willing to sell the securities for is above the top or below the bottom price. The resilience of the market is another aspect we want to consider when assessing the liquidity of a market because a more resilient market is able to absorb oversized trades without causing too much price volatility. In plotting the graph, I calculated the resilience as the spread between the daily weighted average price and the second quartile price, as it represent the central point in the price distribution. As the plot suggests this difference is higher for Finnie-Mae and Freddie-Mac than for Ginnie-Mae: a higher deviation from the second quartile price indicates that there is a concentration of trading activity or price movements at one end of the price spectrum. This can result in price volatility and instability, as a few trades or price spikes have a disproportionate impact on the average price. In other words it indicates that prices are more likely to experience rapid fluctuations, making it difficult to predict and stabilize price levels. That being said about the Amihud factor, market depth and resilience, to have a well-rounded view of the liquidity in RMBS market, the fourth chart relates to Interdealer trades. Dealers, or market makers, play a crucial role in providing liquidity to financial markets by standing ready to buy or sell assets. They absorb customer order imbalances, which occur when there is an excess of buy or sell orders in the market. In our case instead of absorbing customer order imbalances, dealers engage in interdealer trades to spread these imbalances across the other dealer in the system. In other words, they distribute the imbalances among other market-making firms rather than holding them on their own books. This spreading of order imbalances indicates that dealers are less willing to bear the full risk and potential costs associated with absorbing imbalances, potentially resulting in less available liquidity in the market. Therefore, a higher percentage of interdealer trades is indicative of higher reluctance to provide markets with liquidity. In our plot we can see a ramping-up of interdealer trade exactly from 2019 when the massive HTM reclassification by BofA-Citi-JP-MS began confirming once again that an increase in HTM reclassification greatly reduced the liquidity in the markets.

At last, I analyzed the impact that the reduced liquidity has had on the Trading Revenues of BofA-Citi-JP-MS by the means of the regression model outlined above. As the regression output shows, the UMBS variable, which is the sum of Finnie-Mae and Freddie-Mac, is quite significant at a confidence level of 95% for the period 2018-2021 and 99% for the period ending in 2022. The sign of the parameter is relevant as well, as it is negative, correctly indicating that as Finnie-Mae and Freddie-Mac HTM reclassification increases, the trading revenues for the banks decreases, supporting my initial assumption that as HTM reclassification increases the trading revenues decreases, as the trading revenues can be seen as the compensation for bank for providing markets with liquidity. As we can see from the graph below, which represent the yearly variation in trading revenues for BofA-Citi-JP-MS, as soon as the HTM reclassification began we can see that trading revenues decrease significantly.

Figure 5.4: Trading Revenues for BofA-Citi-JP-MS



Findings summary: At last, liquidity is another crucial aspect we want to consider when analyzing the effects of the HTM reclassification. This is because once securities are reclassified as HTM they are locked-up and cannot be sold as freely as they would under AFS or HFT, thus this has implications on the liquidity of the markets. As far as the data I gathered concern, from 2018 to 2022 the HTM over total assets grew from 2% to almost 10% for the four banks BofA-Citi-JP-MS, taking away from markets roughly $5bn of liquidity in 2018 to almost $35bn at the end of 2022. Therefore in an attempt to study the effects that this reclassification had on market liquidity I firstly regressed the trading volume relating to Finnie-Mae and Freddie-Mac (as thy are the asset classes reclassified the most to HTM) against the average HTM scalded by total assets of BofA-Citi-JP-MS and I have found that the reclassification carried out by these banks significantly affected the volumes of trades for Finnie-Mae and Freddie-Mac. Subsequently I performed the regression analysis with number of trades as a dependent variable and as I was expecting the number of trades for these asset classes dropped in the same fashion as the volume of trades. I then thought to back-test my analysis by regressing the volume of trades and the number of trades against the average HTM scaled by total assets of Citizens,HSBC and all those remaining banks with below average HTM reclassification and I found, correctly, that the reclassification carried out by these banks did not impacted the liquidity of markets. As a results of this analysis I then moved on to study the main liquidity indices, which are the Amihud illiquidity factor, market depth, resilience and interdealer trades. What I found is that for Finnie-Mae and Freddie-Mac the degree if illiquidity is way higher than it is for Ginnie-Mae; this translates into a lower market depth and lower resilience for Finnie-Mae and Freddie-Mac compared to Ginnie-Mae. In other words, for Finnie-Mae and Freddie-Mac the market is not very deep and this is concerning because investors are not able to convert quickly in cash their positions if the price they are willing to sell the securities for is above the top or below the bottom prices. Also, for those asset classes there is substantial price volatility and instability, as a few trades or price spikes have a disproportionate impact on the average price, making it difficult to predict and stabilize price levels. Interdealer trades are of importance too as a higher percentage of interdealer trades is indicative of higher reluctance to provide markets with liquidity. Dealers, or market makers, play a crucial role in providing liquidity to financial markets by standing ready to buy or sell assets. They absorb customer order imbalances, which occur when there is an excess of buy or sell orders in the market. In our case instead of absorbing customer order imbalances, dealers engage in interdealer trades to spread these imbalances across the other dealer in the system indicating that dealers are less willing to bear the full risk and potential costs associated with absorbing those imbalances, potentially resulting in less available liquidity in the market. As last step in my liquidity analysis I then regressed trading revenues against Finnie-Mae and Freddie-Mac trading volume and, as I was expecting, I found that as HTM reclassification increases, the trading revenues for the banks decreases, supporting my initial assumption that as HTM reclassification increases the trading revenues decreases, as they can be seen as the compensation for banks for providing markets with liquidity.

Chapter 6

Final Considerations

In conclusion, however, I would not be honest if I would not admit that my analysis is far for being complete. This topic is exceptionally wide and deep and there would be quite a few topics that would be interesting enough to study more in depth. If I could suggests some of them to continue what I have began here, I would probably suggest to study the implications that the HTM reclassification may have had on the profitability of banks. Under an accounting point of view we know that all those unrealized gain and losses flows into the Equity section of the balance sheet by the means of the AOCI reserve: as the HTM reclassification distort the flows of unrealized gain and losses, I would expect the profitability to be strongly influenced, by making banks appear more profitable in period of market distress and less profitable in period of market growth.

Moreover my data sample size was composed exclusively by Advanced Approach banks, banks for which the removal of the AOCI filter has been passed by US regulators. As such all the unrealized gain and losses are now included in full into the regulatory capital. However, apart from these 11 banks I analyzed, all the other banks in the system are non AA. However, some voluntarily adopted the approach by accepting to remove the AOCI filter. Therefore, even if it would a far more complex and articulated analysis, I think it would be exceptionally interesting to look at the investment portfolio, in terms of risk exposure, and funding source composition of these nonAA banks who voluntarily remove the AOCI filter versus those who are of similar size but do not opt for such policy. Different from the mandatory requirement, the voluntary choice has a signaling or commitment purpose and it would be intriguing to see how those banks are moving during this period of market turmoil compared to the other lot of banks that decided to keep the filter.

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Appendix A

The accounting from AFS to HTM

Suppose that at the beginning of year 1, a firm acquires a single credit-riskless fixed-rate financial asset (a loan) that pays \$10 at end of each of years 1-3. The firm holds the loan for the 3 years. Given a market interest rate of 10% at that time, the value of the loan at initiation is \$10/1.1 + \$10/1.1^2 + \$10/1.1^3 = \$24.87. The loan amortization schedule under AC is:

Table A.1: The accounting of the change from AFS to HTM

Year	1	2	3
Beginning balance	\$24.87	\$17.36	\$9.09
+ interest revenue	\$2.49	\$1.74	\$0.91
- cash receipt	\$10.00	\$10.00	\$10.00
Ending balance	\$17.36	\$9.09	-

Let's assume now that a change in the relevant market rate to 12% at the end of year 1 is reflected in fair value. End of year 1 balance = \$16.90 = 10/1.12+10/1.12^2. The interest rate change yields a loss of \$0.46 (\$17.36 - \$16.90). The loan amortization schedule under FV is:

Year	1	2	3
Beginning balance	\$24.87	\$16.90	\$8.93
+ interest revenue	\$2.49	\$2.03	\$1.07
- cash receipt	\$10.00	\$10.00	\$10.00
+ gain	-\$0.46	-	-
Ending balance	\$16.90	\$8.93	-
Income (interest + gain)	\$2.03	\$2.03	\$1.07

If we assume the fixed rate financial asset in the previous example is classified as an

AFS security at the beginning of year 1 and then reclassified to HTM at the end of year 1, the Accretion will be:

Table A.2: Accretion

Year	1	2	3
Ending amortized cost as if the security stayed AFS	$17.36	$9.09	-
- Amortized cost after transfer to HTM (= expected FV)	$16.90	$8.93	-
AOCI balance	- $0.46	- $0.16	-
Accretion (int. revenue at FV - at AC)	-	$ 0.29	$ 0.16

Table A.3: Transfer from AFS to HTM: Journal entries with accretion

Year 1 (AFS to HTM transfer)		
HTM (cost basis)	$16.90	
AFS securities (value accretion)	$0.46	
AFS securities (cost basis)		$17.36
Year 2		
Cash	$10.00	
AOCI accretion		$0.29
Interest revenue		$1.74
HTM securities (cost basis)		$7.97
Year 3		
Cash	$10.00	
AOCI accretion		$0.16
Interest revenue		$0.91
HTM securities (cost basis)		$8.93

Interest revenue in years 2 and 3 is the same as if the securities had remained AFS. Accretion enables the amortized cost basis of HTM securities to rise over time reflecting the 12% relevant market rate at the time of the transfer while interest revenue is calculated using the 10% initial effective rate.

Appendix B

Variables calculation

Table B.1: List of Variables

HTM	BHCT3547 + BHCK8496 + BHCKG300 + BHCKG304 + BHCKG312 + BHCKG320 + BHCKK142 + BHCKK150 + BHCKK154 + BHCKO26 + BHCKHT58
Total Assets	BHCK2170
Overall HTM	average of all the HTM securities per bank for the same period divided by Total Assets
Overall NII	BHCK4074
NII volatility	NII quarter year t / NII quarter year t-1
Net Income	BHCK4340
ROA	Net income / Tot Assets
BV Equity	BHCK3210
Leverage	Total Assets / BV Equity
AFS unrealized gain/(losses)	BHCK1773 - BHCK1772

RMBS HTM	BHCKG300 + BHCKG304 + BHCKG308 +BHCKG312 + BHCKG316 + BHCKG320 + BHCKG380
RMBS AFS	BHCKG303 + BHCKG307 + BHCKG311 + BHCKG315 + BHCKG319 + BHCKG323
CMBS HTM	BHCKK142 + BHCKK146 + BHCKK150 + BHCKK154
CMBS AFS	BHCKK145 + BHCKK149 + BHCKK153 + BHCKK157
ABS HTM	BHCKB838 + BHCKB842 + BHCKB846 + BHCKB850 + BHCKB854 + BHCKB858
ABS AFS	BHCKB841 + BHCKB845 + BHCKB849 + BHCKB853 + BHCKB857 + BHCKB861

Tier2 Capital	BHCA5311
Volatility	St.dev of 4 quarterly Tier2 divided by the their average
Total Loans	BHCK2122
Loan growth	(Total Loan quarter t / Total loan quarter t year-1) - 1
Loan risk	(0.2*BHCKS415 + 0.5*BHCKS416 + 1*BHCKS417 + 1.5*BHCKS429 + 1*BHCKS436+ 1.5*BHCKS437 + 0.2*BHCKS441 + 0.5*BHCKS442 + 1*BHCKS443 + 1.5*BHCKS447 + 1.5*BHCKS455 + 0.2*BHCKS460 + 0.5*BHCKS461 + 1*BHCKS462 + 1.5*BHCKS463) / BHCK2122
RWAs	BHCAA223
Regulatory capital	BHCA3722
CAR	Regulatory capital / RWAs
AFS securities	BHCK1773
AFS risk	(1.5*BHCKS403 + 0.2*BHCKD968 + 0.5*BHCKD969 + 1*BHCKD970) / BHCK1773

$\lvert r_t \rvert$	Absolute value of the daily return
Average Dollar Value	Number of trades * Weighted average daily price
Amihud Ill. factor	$\lvert r_t \rvert$ / ADV
Market Depth	Average Top 5 trades prices - Average Bottom 5 trades prices
Market Resilience	Daily Weighted Average price - 2nd Quartile price
Trading Revenues	BHCKA220
Trading Assets	BHCK3545

The link to each NIC bank profile are:

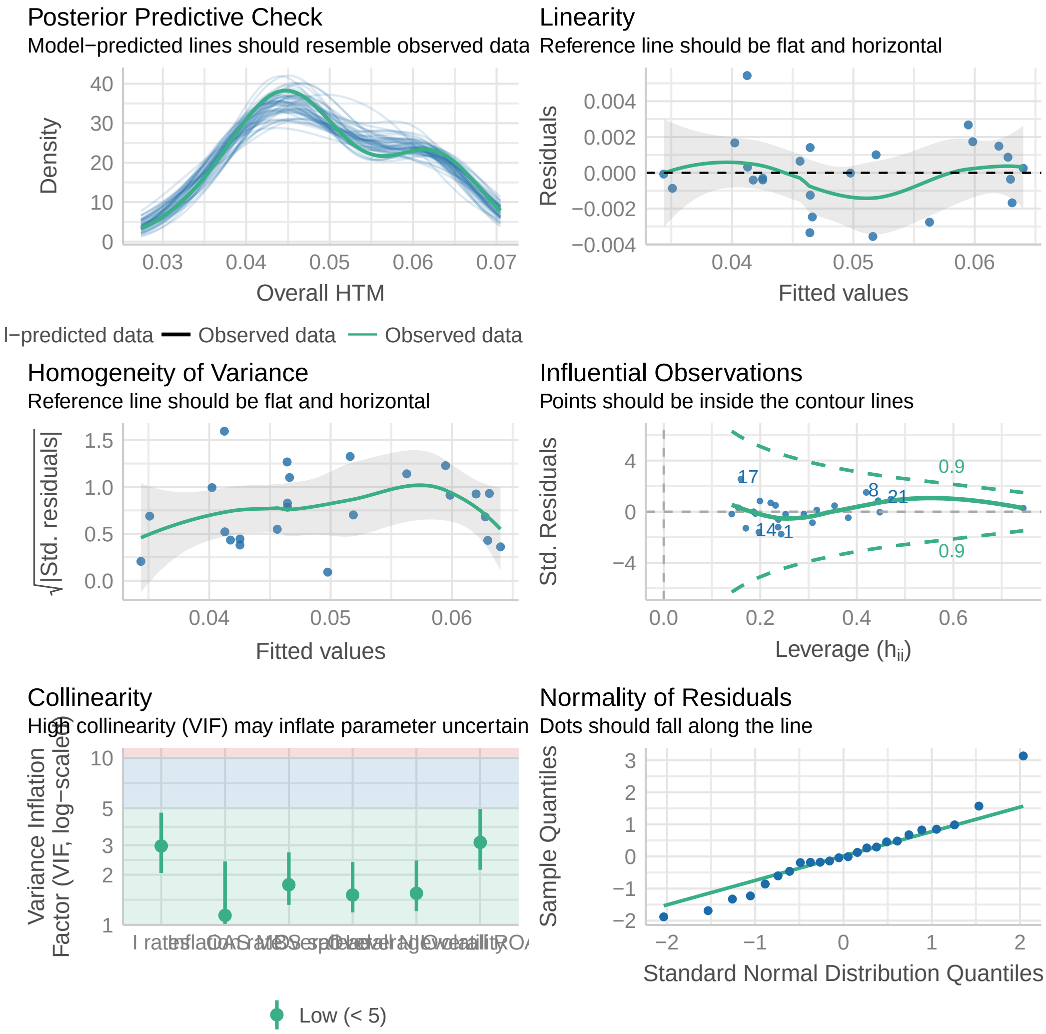
Truist	https://www.ffiec.gov/npw/Institution/Profile/1074156?dt=20191207
Bank of America	https://www.ffiec.gov/npw/Institution/Profile/1073757?dt=20141231
Citibank	https://www.ffiec.gov/npw/Institution/Profile/1951350?dt=20170701
Citizensbank	https://www.ffiec.gov/npw/Institution/Profile/1132449?dt=20190102
HSBC	https://www.ffiec.gov/npw/Institution/Profile/3232316?dt=20160701
JPMorgan	https://www.ffiec.gov/npw/Institution/Profile/1039502?dt=20190519
Morgan Stanley	https://www.ffiec.gov/npw/Institution/Profile/2162966?dt=20220101
BNY Mellon	https://www.ffiec.gov/npw/Institution/Profile/3587146?dt=20180716
StateStreet	https://www.ffiec.gov/npw/Institution/Profile/1111435?dt=20151231
USBancorp	https://www.ffiec.gov/npw/Institution/Profile/1119794?dt=20221201
WellsFargo	https://www.ffiec.gov/npw/Institution/Profile/1120754?dt=20200331

FNMA, FHLMC, GNMA daily trade Data	https://www.finra.org/finra-data/browse-catalog/structured-product-activity-reports-and-tables/historic-reports
MBS market Data	https://www.sifma.org/resources/research/us-mortgage-backed-securities-statistics/

Appendix C

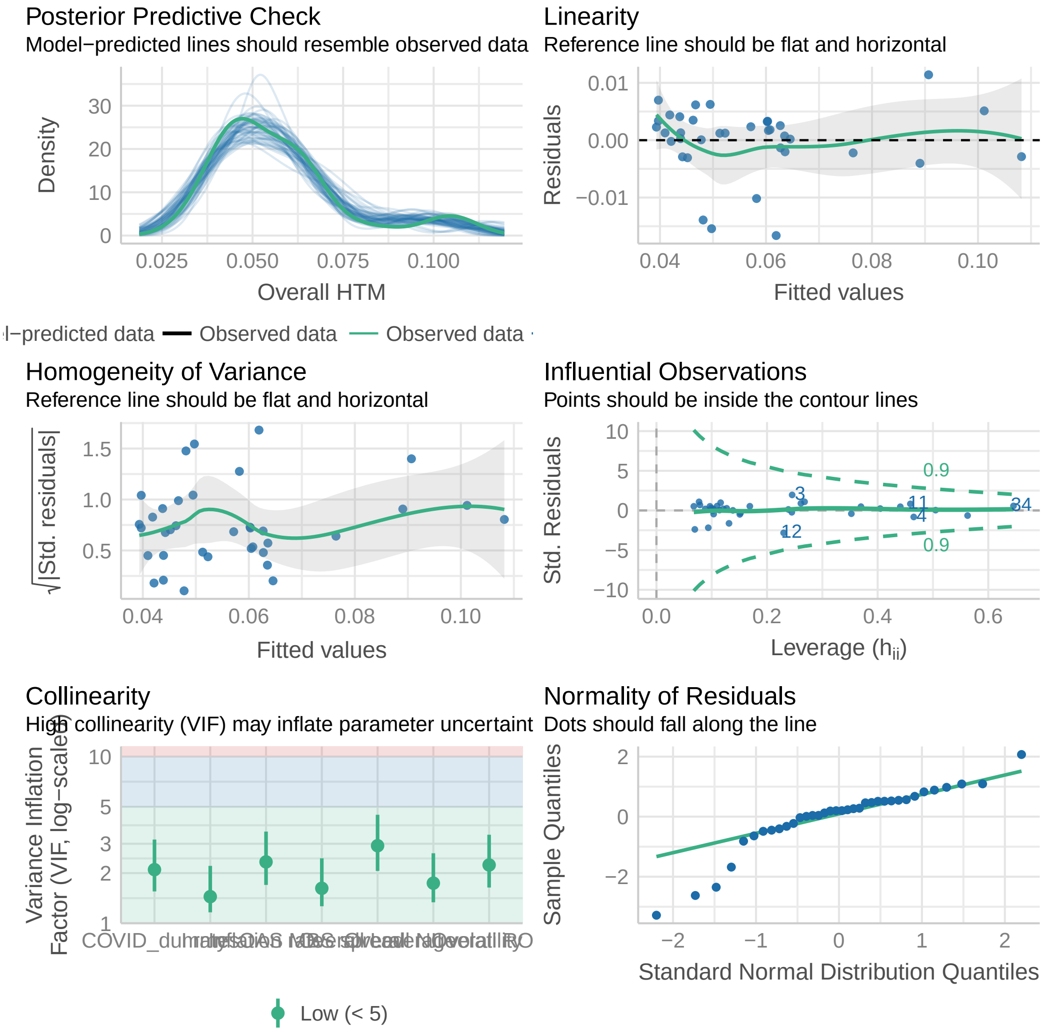
Statistical significance of the three general models

Figure C.1: Before Covid statistical significance test



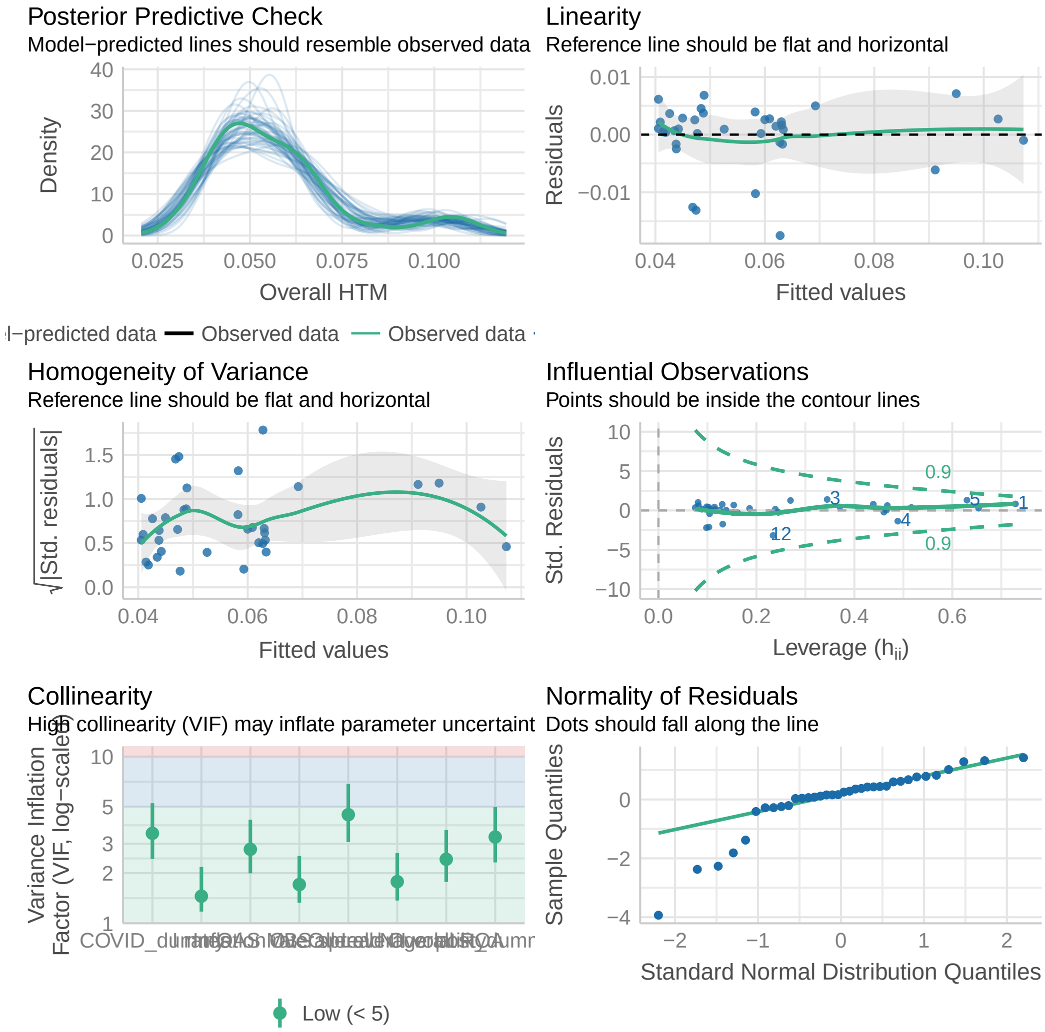

```
## OK: residuals appear as normally distributed (p = 0.762).
## OK: Error variance appears to be homoscedastic (p = 0.651).
##                `I rates` `Overall NII volatility`            `Overall ROA`
##                 2.970791                 1.546901                 3.123241
##       `Overall Leverage`         `Inflation rate`          `OAS MBS spread`
##                 1.510222                 1.139876                 1.740505
##
##  studentized Breusch-Pagan test
##
## data:  nodummiesfit1_reg
## BP = 1.5274, df = 6, p-value = 0.9577
```

Figure C.2: Covid statistical significance test




```
## Warning: Non-normality of residuals detected (p = 0.002).
## OK: Error variance appears to be homoscedastic (p = 0.716).
##                `I rates` `Overall NII volatility`            `Overall ROA`
##                 1.445187                1.740745                 2.237599
##       `Overall Leverage`          `Inflation rate`          `OAS MBS spread`
##                 2.919984                2.335007                 1.621169
##              COVID_dummy
##                 2.098240
##
##  studentized Breusch-Pagan test
##
## data:  Covidonlyfit1_reg
## BP = 1.8898, df = 7, p-value = 0.9657
```

Figure C.3: Post Covid statistical significance test




```
## Warning: Non-normality of residuals detected (p < .001).
## OK: Error variance appears to be homoscedastic (p = 0.885).
##                `I rates` `Overall NII volatility`            `Overall ROA`
##                 1.453918                 1.777420                 2.421186
##       `Overall Leverage`         `Inflation rate`         `OAS MBS spread`
##                 4.483423                 2.778548                 1.707875
##               COVID_dummy               post_dummy
##                 3.464371                 3.291453
##
##  studentized Breusch-Pagan test
##
## data:  overallfit1_reg
## BP = 2.585, df = 8, p-value = 0.9576
```

Appendix D

Bank-based Regressions

D.1 No Dummies regressions

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = bofa1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -1.450e-03 -4.174e-04 -2.315e-05  2.769e-04  1.446e-03
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -3.016e-03  3.575e-03  -0.844  0.41051
## `I rates`         2.796e+00  3.076e+00   0.909  0.37601
## `NII volatility`  1.593e-02  5.144e-02   0.310  0.76061
## ROA               4.288e+01  1.253e+01   3.424  0.00324 **
## Leverage          4.676e-05  4.128e-05   1.133  0.27304
## `Inflation rate` -9.613e+00  8.623e+00  -1.115  0.28042
## `OAS MBS spread` -5.773e-08  3.766e-07  -0.153  0.87995
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0008152 on 17 degrees of freedom
## Multiple R-squared:  0.9201,Adjusted R-squared:  0.8919
## F-statistic: 32.62 on 6 and 17 DF,  p-value: 2.024e-08
## OK: residuals appear as normally distributed (p = 0.292).
## OK: Error variance appears to be homoscedastic (p = 0.163).
##        `I rates` `NII volatility`              ROA         Leverage
##        13.386985         1.418416         9.450620         1.985040
## `Inflation rate` `OAS MBS spread`
##         1.160953         1.945660
##
##  studentized Breusch-Pagan test
```

```
##
## data:  bofa1_reg
## BP = 8.0191, df = 6, p-value = 0.2367
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = citi1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0078813 -0.0018445  0.0000222  0.0015777  0.0113637
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.0254524  0.0187518   1.357   0.1924
## `I rates`         1.3995237  0.1791766   7.811 5.05e-07 ***
## `NII volatility` -0.0872723  0.0398689  -2.189   0.0428 *
## ROA              -0.0499565  0.2354555  -0.212   0.8345
## Leverage         -0.0021783  0.0022964  -0.949   0.3561
## `Inflation rate` -0.3689646  0.4679976  -0.788   0.4413
## `OAS MBS spread`  0.0001206  0.0001694   0.712   0.4864
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.004282 on 17 degrees of freedom
## Multiple R-squared:  0.8765,Adjusted R-squared:  0.8329
## F-statistic: 20.11 on 6 and 17 DF,  p-value: 7.499e-07
## OK: residuals appear as normally distributed (p = 0.082).
## OK: Error variance appears to be homoscedastic (p = 0.379).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.922342         2.611430         1.397734         4.702445
## `Inflation rate` `OAS MBS spread`
##         1.072125         1.803139
##
##  studentized Breusch-Pagan test
##
## data:  citi1_reg
## BP = 9.6325, df = 6, p-value = 0.141
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = citizens1)
##
## Residuals:
```

```
##        Min         1Q     Median         3Q        Max
## -0.0040709 -0.0007447  0.0000258  0.0008997  0.0042901
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       8.380e-02  1.612e-02   5.198 7.25e-05 ***
## `I rates`        -4.874e-01  1.235e-01  -3.947  0.00104 **
## `NII volatility`  3.628e-02  1.266e-02   2.866  0.01071 *
## ROA              -1.381e-01  2.415e-01  -0.572  0.57497
## Leverage         -5.856e-03  2.199e-03  -2.663  0.01640 *
## `Inflation rate`  3.199e-02  2.243e-01   0.143  0.88827
## `OAS MBS spread` -1.336e-04  7.888e-05  -1.694  0.10860
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.002077 on 17 degrees of freedom
## Multiple R-squared:  0.9385,Adjusted R-squared:  0.9167
## F-statistic:  43.2 on 6 and 17 DF,  p-value: 2.275e-09
## OK: residuals appear as normally distributed (p = 0.721).
## OK: Error variance appears to be homoscedastic (p = 0.651).
##        `I rates` `NII volatility`              ROA         Leverage
##         5.899542         1.418451         2.521504         3.401854
## `Inflation rate` `OAS MBS spread`
##         1.047156         1.661450
##
##  studentized Breusch-Pagan test
##
## data:  citizens1_reg
## BP = 11.13, df = 6, p-value = 0.08443
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = hsbc1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.036553 -0.006279  0.003271  0.007901  0.018178
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.1314298  0.0332532   3.952  0.00103 **
## `I rates`         1.1248170  0.8244060   1.364  0.19023
## `NII volatility`  0.0237613  0.0733981   0.324  0.75009
## ROA              -1.1007145  4.1354433  -0.266  0.79331
## Leverage         -0.0107852  0.0040605  -2.656  0.01663 *
## `Inflation rate` -2.5354455  1.9627572  -1.292  0.21372
```

```
## `OAS MBS spread`  0.0007771  0.0007544   1.030  0.31741
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01649 on 17 degrees of freedom
## Multiple R-squared:  0.3733,Adjusted R-squared:  0.1521
## F-statistic: 1.687 on 6 and 17 DF,  p-value: 0.1847
## Warning: Non-normality of residuals detected (p = 0.014).
## OK: Error variance appears to be homoscedastic (p = 0.079).
##        `I rates` `NII volatility`              ROA         Leverage
##         4.170150         2.137210         3.361844         4.555913
## `Inflation rate` `OAS MBS spread`
##         1.271137         2.410038
##
##  studentized Breusch-Pagan test
##
## data:  hsbc1_reg
## BP = 10.319, df = 6, p-value = 0.1119
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + `Inflation rate` +
##     `OAS MBS spread` + Leverage, data = jpmorgan1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0032106 -0.0006416  0.0000596  0.0008799  0.0029051
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       4.187e-02  1.709e-02   2.451  0.02538 *
## `I rates`        -4.027e-01  1.340e-01  -3.005  0.00796 **
## `NII volatility` -1.486e-02  1.312e-02  -1.133  0.27301
## ROA               2.320e-01  6.536e-01   0.355  0.72701
## `Inflation rate` -1.900e-01  1.898e-01  -1.001  0.33087
## `OAS MBS spread`  4.134e-05  7.164e-05   0.577  0.57148
## Leverage         -2.244e-03  1.321e-03  -1.698  0.10776
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.001576 on 17 degrees of freedom
## Multiple R-squared:  0.8644,Adjusted R-squared:  0.8165
## F-statistic: 18.06 on 6 and 17 DF,  p-value: 1.621e-06
## OK: residuals appear as normally distributed (p = 0.997).
## OK: Error variance appears to be homoscedastic (p = 0.295).
##        `I rates` `NII volatility`              ROA `Inflation rate`
##        12.062702         3.068870        11.923344         1.301189
```

```
## `OAS MBS spread`         Leverage
##         2.379856         3.955722
##
##  studentized Breusch-Pagan test
##
## data:  jpmorgan1_reg
## BP = 7.2664, df = 6, p-value = 0.2969
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = ny1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.042543 -0.005456  0.001022  0.014181  0.025807
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.3186807  0.1772578  -1.798  0.08999 .
## `I rates`         5.0652516  1.5758265   3.214  0.00509 **
## `NII volatility`  0.0766289  0.0868825   0.882  0.39009
## ROA               4.5028081  8.0693400   0.558  0.58411
## Leverage          0.0246535  0.0138595   1.779  0.09316 .
## `Inflation rate`  1.1354169  2.3454250   0.484  0.63449
## `OAS MBS spread`  0.0006382  0.0008848   0.721  0.48054
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.021 on 17 degrees of freedom
## Multiple R-squared:  0.8445,Adjusted R-squared:  0.7896
## F-statistic: 15.38 on 6 and 17 DF,  p-value: 4.99e-06
## OK: residuals appear as normally distributed (p = 0.177).
## OK: Error variance appears to be homoscedastic (p = 0.257).
##        `I rates` `NII volatility`              ROA         Leverage
##         9.394644         2.617732        12.050253         3.965069
## `Inflation rate` `OAS MBS spread`
##         1.119171         2.043982
##
##  studentized Breusch-Pagan test
##
## data:  ny1_reg
## BP = 9.764, df = 6, p-value = 0.1349
```

```
##
## Call:
```

```
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = stanley1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0124371 -0.0023464 -0.0002512  0.0027072  0.0185912
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.1187075  0.0722430  -1.643  0.11871
## `I rates`         1.6771892  0.5046109   3.324  0.00402 **
## `NII volatility`  0.0014784  0.0022303   0.663  0.51629
## ROA               1.5825074  2.2809586   0.694  0.49719
## Leverage          0.0082899  0.0060189   1.377  0.18628
## `Inflation rate`  0.4552265  0.8518663   0.534  0.59999
## `OAS MBS spread`  0.0003030  0.0002938   1.031  0.31678
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.007613 on 17 degrees of freedom
## Multiple R-squared:  0.8754,Adjusted R-squared:  0.8315
## F-statistic: 19.91 on 6 and 17 DF,  p-value: 8.056e-07
## OK: residuals appear as normally distributed (p = 0.079).
## OK: Error variance appears to be homoscedastic (p = 0.311).
##        `I rates` `NII volatility`              ROA         Leverage
##         7.331021         1.526022         7.189942         1.620764
## `Inflation rate` `OAS MBS spread`
##         1.123528         1.715059
##
##  studentized Breusch-Pagan test
##
## data:  stanley1_reg
## BP = 7.647, df = 6, p-value = 0.2651
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = truist1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.020918 -0.009457  0.000348  0.007663  0.025833
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.0047744  0.0971716  -0.049   0.9614
## `I rates`        -2.1017893  0.5413071  -3.883   0.0012 **
```

```
## `NII volatility`  0.0066920  0.0175251   0.382   0.7073
## ROA              39.6416051  7.5170351   5.274 6.21e-05 ***
## Leverage          0.0055103  0.0227085   0.243   0.8112
## `Inflation rate`  1.9052853  1.5543939   1.226   0.2370
## `OAS MBS spread` -0.0006233  0.0005232  -1.191   0.2498
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0144 on 17 degrees of freedom
## Multiple R-squared:  0.6913,Adjusted R-squared:  0.5824
## F-statistic: 6.346 on 6 and 17 DF,  p-value: 0.001198
## OK: residuals appear as normally distributed (p = 0.890).
## Warning: Heteroscedasticity (non-constant error variance) detected (p = 0.036).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.359204         1.354746         1.833101         1.049461
## `Inflation rate` `OAS MBS spread`
##         1.046141         1.520898
##
##  studentized Breusch-Pagan test
##
## data:  truist1_reg
## BP = 15.874, df = 6, p-value = 0.01445
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = bancorp1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.041129 -0.008156  0.000644  0.008971  0.019147
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.3857971  0.4441372   0.869  0.39714
## `I rates`        -1.3466083  0.5056272  -2.663  0.01638 *
## `NII volatility`  0.5581478  0.1666995   3.348  0.00381 **
## ROA               5.9423074  8.9887226   0.661  0.51742
## Leverage         -0.0423220  0.0369832  -1.144  0.26833
## `Inflation rate`  0.1929972  1.7216043   0.112  0.91205
## `OAS MBS spread`  0.0002418  0.0006102   0.396  0.69681
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0156 on 17 degrees of freedom
## Multiple R-squared:  0.6141,Adjusted R-squared:  0.4779
## F-statistic: 4.509 on 6 and 17 DF,  p-value: 0.006549
```

```
## Warning: Non-normality of residuals detected (p = 0.003).
## Warning: Heteroscedasticity (non-constant error variance) detected (p < .001).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.751963         1.613766         5.314794         4.261788
## `Inflation rate` `OAS MBS spread`
##         1.092246         1.761100
##
##  studentized Breusch-Pagan test
##
## data:  bancorp1_reg
## BP = 14.964, df = 6, p-value = 0.02053
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread`, data = wells1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0092573 -0.0033418 -0.0007333  0.0034148  0.0089439
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.1865949  0.0722026   2.584   0.0193 *
## `I rates`         1.2685214  0.2327796   5.449 4.33e-05 ***
## `NII volatility`  0.0233824  0.0377036   0.620   0.5434
## ROA              -9.4484280  1.6017781  -5.899 1.75e-05 ***
## Leverage         -0.0043637  0.0062996  -0.693   0.4979
## `Inflation rate` -0.1739221  0.6179820  -0.281   0.7818
## `OAS MBS spread`  0.0002163  0.0002245   0.963   0.3489
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.005587 on 17 degrees of freedom
## Multiple R-squared:  0.9473,Adjusted R-squared:  0.9287
## F-statistic: 50.93 on 6 and 17 DF,  p-value: 6.187e-10
## OK: residuals appear as normally distributed (p = 0.961).
## Warning: Heteroscedasticity (non-constant error variance) detected (p = 0.048).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.896967         1.978497         3.539461         3.536657
## `Inflation rate` `OAS MBS spread`
##         1.097982         1.859188
##
##  studentized Breusch-Pagan test
##
## data:  wells1_reg
## BP = 8.1447, df = 6, p-value = 0.2277
```

D.2 Covid-only dummy bank-based regressions

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = bofa1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0101072 -0.0018720  0.0002397  0.0021589  0.0066926
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -2.953e-02  3.749e-03  -7.877 1.40e-08 ***
## `I rates`        -6.113e+00  4.178e+00  -1.463 0.154616
## `NII volatility`  2.600e-01  6.995e-02   3.718 0.000891 ***
## ROA               8.561e+01  2.665e+01   3.213 0.003298 **
## Leverage          4.126e-04  5.402e-05   7.638 2.55e-08 ***
## `Inflation rate`  2.368e+01  1.023e+01   2.316 0.028109 *
## `OAS MBS spread` -2.384e-06  3.985e-07  -5.983 1.91e-06 ***
## COVID_dummy       7.342e-03  1.956e-03   3.754 0.000810 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.00343 on 28 degrees of freedom
## Multiple R-squared:  0.9683,Adjusted R-squared:  0.9603
## F-statistic:   122 on 7 and 28 DF,  p-value: < 2.2e-16
## OK: residuals appear as normally distributed (p = 0.234).
## OK: Error variance appears to be homoscedastic (p = 0.234).
##        `I rates` `NII volatility`              ROA         Leverage
##         3.910933         4.460357         2.726855         5.077679
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         2.710564         1.353575         1.833143
##
##  studentized Breusch-Pagan test
##
## data:  bofa1_reg
## BP = 10.38, df = 7, p-value = 0.168
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = citi1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0270489 -0.0041054 -0.0001615  0.0063459  0.0206019
```

```
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)       -0.0961685  0.0195795  -4.912 3.53e-05 ***
## `I rates`          0.0156381  0.2378252   0.066  0.94804
## `NII volatility` -0.0531984  0.0140997  -3.773  0.00077 ***
## ROA                0.7323951  0.4755302   1.540  0.13475
## Leverage           0.0145024  0.0023682   6.124 1.31e-06 ***
## `Inflation rate`  0.9458144  0.5373696   1.760  0.08932 .
## `OAS MBS spread` -0.0004137  0.0001187  -3.487  0.00163 **
## COVID_dummy       -0.0100200  0.0073744  -1.359  0.18507
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01027 on 28 degrees of freedom
## Multiple R-squared:  0.9195,Adjusted R-squared:  0.8994
## F-statistic: 45.69 on 7 and 28 DF,  p-value: 1.165e-13
## OK: residuals appear as normally distributed (p = 0.406).
## OK: Error variance appears to be homoscedastic (p = 0.806).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.680466         1.841684         1.087103         4.295860
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         2.195569         1.322027         2.904934
##
##  studentized Breusch-Pagan test
##
## data:  citi1_reg
## BP = 9.7182, df = 7, p-value = 0.2051
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = citizens1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0069290 -0.0021956 -0.0001842  0.0022258  0.0091017
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        1.045e-01  1.051e-02   9.937 1.11e-10 ***
## `I rates`         -2.448e-01  8.922e-02  -2.743   0.0105 *
## `NII volatility`  9.754e-02  8.947e-03  10.902 1.38e-11 ***
## ROA               -4.308e-01  2.328e-01  -1.851   0.0747 .
## Leverage          -9.517e-03  1.617e-03  -5.885 2.49e-06 ***
## `Inflation rate` -1.979e-01  1.680e-01  -1.177   0.2490
## `OAS MBS spread` -6.591e-05  4.266e-05  -1.545   0.1336
```

```
## COVID_dummy      -1.909e-03  2.243e-03  -0.851   0.4020
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.003436 on 28 degrees of freedom
## Multiple R-squared:  0.9177,Adjusted R-squared:  0.8971
## F-statistic:  44.6 on 7 and 28 DF,  p-value: 1.584e-13
## OK: residuals appear as normally distributed (p = 0.667).
## OK: Error variance appears to be homoscedastic (p = 0.595).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.114514         3.379185         1.577804         4.324098
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         1.919862         1.527536         2.403323
##
##  studentized Breusch-Pagan test
##
## data:  citizens1_reg
## BP = 6.6672, df = 7, p-value = 0.4643
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = hsbc1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.044293 -0.002502  0.001265  0.005239  0.018937
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.1128013  0.0194262   5.807 3.08e-06 ***
## `I rates`         0.9084280  0.4274275   2.125   0.0425 *
## `NII volatility`  0.0138053  0.0395806   0.349   0.7299
## ROA               0.8647964  1.8732400   0.462   0.6479
## Leverage         -0.0073295  0.0020834  -3.518   0.0015 **
## `Inflation rate` -0.7195740  0.6851749  -1.050   0.3026
## `OAS MBS spread`  0.0002268  0.0002190   1.036   0.3091
## COVID_dummy       0.0071586  0.0101371   0.706   0.4859
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01388 on 28 degrees of freedom
## Multiple R-squared:  0.6023,Adjusted R-squared:  0.5029
## F-statistic: 6.058 on 7 and 28 DF,  p-value: 0.00023
## Warning: Non-normality of residuals detected (p < .001).
## OK: Error variance appears to be homoscedastic (p = 0.354).
##        `I rates` `NII volatility`              ROA         Leverage
```

```
##         2.975113         3.898391         2.777983         4.051723
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         1.956448         2.466918         3.008723
##
##  studentized Breusch-Pagan test
##
## data:  hsbc1_reg
## BP = 5.8921, df = 7, p-value = 0.5524
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + `Inflation rate` +
##     `OAS MBS spread` + Leverage + COVID_dummy, data = jpmorgan1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0195082 -0.0057279 -0.0005629  0.0052211  0.0237987
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -1.660e-01  2.696e-02  -6.156 1.20e-06 ***
## `I rates`        -1.600e+00  4.096e-01  -3.907 0.000539 ***
## `NII volatility`  2.105e-01  3.691e-02   5.704 4.07e-06 ***
## ROA               4.321e+00  1.553e+00   2.782 0.009554 **
## `Inflation rate`  1.160e+00  5.521e-01   2.101 0.044794 *
## `OAS MBS spread` -7.313e-05  1.342e-04  -0.545 0.590151
## Leverage          1.416e-02  2.331e-03   6.072 1.51e-06 ***
## COVID_dummy       1.094e-02  6.904e-03   1.585 0.124139
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01018 on 28 degrees of freedom
## Multiple R-squared:  0.9309,Adjusted R-squared:  0.9136
## F-statistic: 53.89 on 7 and 28 DF,  p-value: 1.416e-14
## OK: residuals appear as normally distributed (p = 0.939).
## OK: Error variance appears to be homoscedastic (p = 0.470).
##        `I rates` `NII volatility`              ROA `Inflation rate`
##         5.074098         5.547593         2.709155         2.359528
## `OAS MBS spread`         Leverage      COVID_dummy
##         1.722064         3.104049         2.592614
##
##  studentized Breusch-Pagan test
##
## data:  jpmorgan1_reg
## BP = 11.14, df = 7, p-value = 0.1326
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = ny1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.079918 -0.021999 -0.001101  0.020472  0.082693
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.2187382  0.1339153  -1.633 0.113580
## `I rates`         3.3190881  0.8264923   4.016 0.000403 ***
## `NII volatility`  0.0042463  0.0502787   0.084 0.933295
## ROA               4.4934703  4.9812518   0.902 0.374711
## Leverage          0.0154335  0.0115853   1.332 0.193548
## `Inflation rate`  5.1606669  1.4815373   3.483 0.001646 **
## `OAS MBS spread`  0.0003547  0.0003959   0.896 0.377935
## COVID_dummy       0.0593011  0.0183287   3.235 0.003113 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03319 on 28 degrees of freedom
## Multiple R-squared:  0.7128,Adjusted R-squared:  0.641
## F-statistic: 9.928 on 7 and 28 DF,  p-value: 3.522e-06
## OK: residuals appear as normally distributed (p = 0.155).
## OK: Error variance appears to be homoscedastic (p = 0.147).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.944741         1.908565         2.821596         3.006303
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         1.599176         1.410376         1.719563
##
##  studentized Breusch-Pagan test
##
## data:  ny1_reg
## BP = 14.64, df = 7, p-value = 0.0409
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = stanley1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0153123 -0.0035943 -0.0004135  0.0054286  0.0135376
##
## Coefficients:
```

```
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -2.425e-01  4.312e-02  -5.624 5.06e-06 ***
## `I rates`         7.121e-01  1.757e-01   4.053 0.000364 ***
## `NII volatility`  1.400e-03  2.064e-03   0.679 0.503015
## ROA               7.386e+00  8.354e-01   8.841 1.36e-09 ***
## Leverage          1.781e-02  4.011e-03   4.440 0.000128 ***
## `Inflation rate`  6.739e-01  3.949e-01   1.706 0.099021 .
## `OAS MBS spread`  7.387e-05  9.102e-05   0.812 0.423882
## COVID_dummy       1.957e-02  4.827e-03   4.054 0.000363 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.008001 on 28 degrees of freedom
## Multiple R-squared:  0.9376,Adjusted R-squared:  0.922
## F-statistic: 60.08 on 7 and 28 DF,  p-value: 3.469e-15
## OK: residuals appear as normally distributed (p = 0.563).
## OK: Error variance appears to be homoscedastic (p = 0.261).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.512235         1.265763         2.525365         1.230881
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         1.955220         1.282553         2.051848
##
##  studentized Breusch-Pagan test
##
## data:  stanley1_reg
## BP = 8.4908, df = 7, p-value = 0.2913
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = state1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.033473 -0.016367 -0.000827  0.014230  0.055828
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.0964980  0.0939161   1.027  0.31298
## `I rates`          2.3133789  0.6831224   3.386  0.00211 **
## `NII volatility` -0.0068704  0.0129392  -0.531  0.59962
## ROA               12.1343756  7.7986386   1.556  0.13095
## Leverage          -0.0094347  0.0044771  -2.107  0.04417 *
## `Inflation rate`   2.8952167  0.9938553   2.913  0.00696 **
## `OAS MBS spread`   0.0001323  0.0002841   0.466  0.64513
## COVID_dummy        0.0452264  0.0114716   3.942  0.00049 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02406 on 28 degrees of freedom
## Multiple R-squared:  0.7612,Adjusted R-squared:  0.7015
## F-statistic: 12.75 on 7 and 28 DF,  p-value: 3.087e-07
## OK: residuals appear as normally distributed (p = 0.564).
## OK: Error variance appears to be homoscedastic (p = 0.612).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.527965         1.348156         2.660620         2.031083
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         1.369327         1.381424         1.281724
##
##  studentized Breusch-Pagan test
##
## data:  state1_reg
## BP = 7.1628, df = 7, p-value = 0.4121
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = truist1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.094865 -0.004968  0.002271  0.015459  0.025044
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.0121727  0.0807825  -0.151    0.881
## `I rates`        -0.7062930  0.6463261  -1.093    0.284
## `NII volatility`  0.0118599  0.0236439   0.502    0.620
## ROA              20.6053647 12.2783488   1.678    0.104
## Leverage          0.0115340  0.0179004   0.644    0.525
## `Inflation rate` -0.1713810  1.2716232  -0.135    0.894
## `OAS MBS spread`  0.0001099  0.0003407   0.323    0.749
## COVID_dummy      -0.0939658  0.0150310  -6.251 9.33e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02541 on 28 degrees of freedom
## Multiple R-squared:  0.7269,Adjusted R-squared:  0.6587
## F-statistic: 10.65 on 7 and 28 DF,  p-value: 1.817e-06
## Warning: Non-normality of residuals detected (p < .001).
## OK: Error variance appears to be homoscedastic (p = 0.130).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.029712         3.494393         2.080987         1.937433
## `Inflation rate` `OAS MBS spread`      COVID_dummy
```

```
##         2.010642         1.782578         1.973689
##
##  studentized Breusch-Pagan test
##
## data:  truist1_reg
## BP = 3.9422, df = 7, p-value = 0.7864
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = bancorp1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.060757 -0.006665  0.001340  0.008442  0.028760
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.0493087  0.1051842   0.469  0.64285
## `I rates`        -1.3255081  0.4305344  -3.079  0.00462 **
## `NII volatility`  0.4217240  0.0849636   4.964 3.06e-05 ***
## ROA               6.3263469  3.8267338   1.653  0.10946
## Leverage         -0.0051616  0.0067910  -0.760  0.45357
## `Inflation rate` -0.0911648  0.8563322  -0.106  0.91598
## `OAS MBS spread`  0.0001760  0.0002204   0.798  0.43148
## COVID_dummy      -0.0587681  0.0126372  -4.650 7.21e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01627 on 28 degrees of freedom
## Multiple R-squared:  0.8934,Adjusted R-squared:  0.8668
## F-statistic: 33.54 on 7 and 28 DF,  p-value: 5.531e-12
## Warning: Non-normality of residuals detected (p < .001).
## OK: Error variance appears to be homoscedastic (p = 0.575).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.196489         5.171125         6.260035         6.997001
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         2.223745         1.819713         3.402415
##
##  studentized Breusch-Pagan test
##
## data:  bancorp1_reg
## BP = 10.249, df = 7, p-value = 0.1749
```

```
##
## Call:
```

```
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy, data = wells1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0243830 -0.0088251 -0.0004712  0.0076535  0.0219905
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.1537979  0.0812825  -1.892 0.068855 .
## `I rates`         0.6586814  0.2851058   2.310 0.028456 *
## `NII volatility` -0.0005605  0.0276535  -0.020 0.983973
## ROA              -5.4411395  1.6185988  -3.362 0.002255 **
## Leverage          0.0298496  0.0073374   4.068 0.000350 ***
## `Inflation rate`  3.3906615  0.6114101   5.546 6.26e-06 ***
## `OAS MBS spread` -0.0006519  0.0001698  -3.840 0.000643 ***
## COVID_dummy      -0.0241825  0.0126085  -1.918 0.065368 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01293 on 28 degrees of freedom
## Multiple R-squared:  0.9202,Adjusted R-squared:  0.9003
## F-statistic: 46.14 on 7 and 28 DF,  p-value: 1.03e-13
## OK: residuals appear as normally distributed (p = 0.935).
## OK: Error variance appears to be homoscedastic (p = 0.775).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.525815         2.631131         6.813125         4.420203
## `Inflation rate` `OAS MBS spread`      COVID_dummy
##         1.795733         1.709195         5.365215
##
##  studentized Breusch-Pagan test
##
## data:  wells1_reg
## BP = 7.1708, df = 7, p-value = 0.4113
```

D.3 Both Dummies bank-based regressions

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = bofa1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0070686 -0.0017633  0.0001023  0.0014921  0.0067316
```

```
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -3.291e-02  3.608e-03  -9.121 9.84e-10 ***
## `I rates`        -1.152e+01  4.269e+00  -2.698  0.01187 *
## `NII volatility`  3.546e-01  7.218e-02   4.913 3.85e-05 ***
## ROA               1.052e+02  2.513e+01   4.187  0.00027 ***
## Leverage          4.326e-04  4.934e-05   8.767 2.21e-09 ***
## `Inflation rate`  3.764e+01  1.058e+01   3.559  0.00140 **
## `OAS MBS spread` -2.020e-06  3.841e-07  -5.259 1.52e-05 ***
## COVID_dummy       3.296e-03  2.313e-03   1.425  0.16570
## post_dummy       -1.040e-02  3.842e-03  -2.708  0.01160 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.003098 on 27 degrees of freedom
## Multiple R-squared:  0.975,Adjusted R-squared:  0.9676
## F-statistic: 131.8 on 8 and 27 DF,  p-value: < 2.2e-16
## OK: residuals appear as normally distributed (p = 0.933).
## OK: Error variance appears to be homoscedastic (p = 0.963).
##        `I rates` `NII volatility`              ROA         Leverage
##         5.005775         5.824465         2.973721         5.193318
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         3.555050         1.542413         3.145004         4.229190
##
##  studentized Breusch-Pagan test
##
## data:  bofa1_reg
## BP = 14.928, df = 8, p-value = 0.06057
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = citi1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0267736 -0.0041094 -0.0005577  0.0062555  0.0219796
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.0925597  0.0222072  -4.168 0.000283 ***
## `I rates`         0.0581823  0.2681917   0.217 0.829884
## `NII volatility` -0.0496360  0.0173269  -2.865 0.007984 **
## ROA               0.7366532  0.4832042   1.525 0.139008
## Leverage          0.0141558  0.0025860   5.474 8.55e-06 ***
```

```
## `Inflation rate`  0.8636747  0.5903663   1.463 0.155026
## `OAS MBS spread` -0.0004268  0.0001257  -3.395 0.002139 **
## COVID_dummy      -0.0082910  0.0088608  -0.936 0.357722
## post_dummy        0.0046324  0.0126792   0.365 0.717693
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01044 on 27 degrees of freedom
## Multiple R-squared:  0.9199,Adjusted R-squared:  0.8962
## F-statistic: 38.76 on 8 and 27 DF,  p-value: 7.741e-13
## OK: residuals appear as normally distributed (p = 0.091).
## OK: Error variance appears to be homoscedastic (p = 0.834).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.070867         2.695172         1.087735         4.964078
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.567980         1.437954         4.064213         4.058447
##
##  studentized Breusch-Pagan test
##
## data:  citi1_reg
## BP = 11.541, df = 8, p-value = 0.1729
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = citizens1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0058302 -0.0021266 -0.0002272  0.0017074  0.0098907
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.216e-01  1.438e-02   8.457 4.54e-09 ***
## `I rates`        -1.572e-01  1.007e-01  -1.560   0.1304
## `NII volatility`  9.824e-02  8.674e-03  11.325 9.23e-12 ***
## ROA              -3.588e-01  2.294e-01  -1.564   0.1294
## Leverage         -1.183e-02  2.081e-03  -5.686 4.86e-06 ***
## `Inflation rate` -3.412e-01  1.835e-01  -1.859   0.0739 .
## `OAS MBS spread` -9.106e-05  4.391e-05  -2.074   0.0478 *
## COVID_dummy       1.039e-03  2.786e-03   0.373   0.7121
## post_dummy        7.280e-03  4.307e-03   1.690   0.1025
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.003327 on 27 degrees of freedom
```

```
## Multiple R-squared:  0.9256,Adjusted R-squared:  0.9035
## F-statistic: 41.97 on 8 and 27 DF,  p-value: 2.924e-13
## OK: residuals appear as normally distributed (p = 0.282).
## OK: Error variance appears to be homoscedastic (p = 0.362).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.875099         3.386726         1.634217         7.638494
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.441128         1.725759         3.952153         4.607977
##
##  studentized Breusch-Pagan test
##
## data:  citizens1_reg
## BP = 6.0967, df = 8, p-value = 0.6364
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = hsbc1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.042725 -0.002501  0.000813  0.006172  0.019595
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.1184631  0.0214447   5.524 7.48e-06 ***
## `I rates`         1.0423653  0.4777762   2.182  0.03801 *
## `NII volatility`  0.0081986  0.0408952   0.200  0.84261
## ROA               0.9255453  1.8948921   0.488  0.62918
## Leverage         -0.0078361  0.0022425  -3.494  0.00166 **
## `Inflation rate` -0.9568915  0.7812702  -1.225  0.23123
## `OAS MBS spread`  0.0001994  0.0002252   0.885  0.38371
## COVID_dummy       0.0102296  0.0112633   0.908  0.37179
## post_dummy        0.0089675  0.0136846   0.655  0.51782
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01402 on 27 degrees of freedom
## Multiple R-squared:  0.6085,Adjusted R-squared:  0.4926
## F-statistic: 5.247 on 8 and 27 DF,  p-value: 0.0005056
## Warning: Non-normality of residuals detected (p < .001).
## OK: Error variance appears to be homoscedastic (p = 0.481).
##        `I rates` `NII volatility`              ROA         Leverage
##         3.641549         4.076840         2.784648         4.598168
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.491877         2.555423         3.638655         2.619462
```

```
##
##  studentized Breusch-Pagan test
##
## data:  hsbc1_reg
## BP = 8.1906, df = 8, p-value = 0.4151
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = jpmorgan1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0186550 -0.0060442 -0.0004714  0.0063470  0.0237864
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -1.799e-01  3.304e-02  -5.445 9.24e-06 ***
## `I rates`        -1.672e+00  4.242e-01  -3.942 0.000516 ***
## `NII volatility`  2.180e-01  3.854e-02   5.656 5.26e-06 ***
## ROA               4.412e+00  1.571e+00   2.809 0.009124 **
## Leverage          1.520e-02  2.738e-03   5.551 6.96e-06 ***
## `Inflation rate`  1.325e+00  5.994e-01   2.210 0.035768 *
## `OAS MBS spread` -2.859e-05  1.481e-04  -0.193 0.848332
## COVID_dummy       8.125e-03  7.932e-03   1.024 0.314763
## post_dummy       -8.416e-03  1.135e-02  -0.741 0.464962
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01027 on 27 degrees of freedom
## Multiple R-squared:  0.9323,Adjusted R-squared:  0.9122
## F-statistic: 46.46 on 8 and 27 DF,  p-value: 8.339e-14
## OK: residuals appear as normally distributed (p = 0.988).
## OK: Error variance appears to be homoscedastic (p = 0.772).
##        `I rates` `NII volatility`              ROA         Leverage
##         5.354885         5.949527         2.725635         4.211425
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.737026         2.061747         3.367026         3.364414
##
##  studentized Breusch-Pagan test
##
## data:  jpmorgan1_reg
## BP = 10.297, df = 8, p-value = 0.2448
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = ny1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.06745 -0.01802 -0.00082  0.01562  0.09652
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.1073925  0.1508366  -0.712 0.482585
## `I rates`         3.4271817  0.8122145   4.220 0.000247 ***
## `NII volatility` -0.0247721  0.0529177  -0.468 0.643452
## ROA               2.9753857  4.9807377   0.597 0.555232
## Leverage          0.0065429  0.0128103   0.511 0.613673
## `Inflation rate`  3.6606660  1.7646091   2.074 0.047693 *
## `OAS MBS spread`  0.0001424  0.0004129   0.345 0.732758
## COVID_dummy       0.0714578  0.0197041   3.627 0.001178 **
## post_dummy        0.0514841  0.0345100   1.492 0.147329
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03249 on 27 degrees of freedom
## Multiple R-squared:  0.7347,Adjusted R-squared:  0.6561
## F-statistic: 9.345 on 8 and 27 DF,  p-value: 4.396e-06
## OK: residuals appear as normally distributed (p = 0.071).
## OK: Error variance appears to be homoscedastic (p = 0.689).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.960342         2.206716         2.944498         3.836591
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.367959         1.600524         2.074325         3.103072
##
##  studentized Breusch-Pagan test
##
## data:  ny1_reg
## BP = 12.128, df = 8, p-value = 0.1456
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = stanley1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
```

```
## -0.0154983 -0.0034412 -0.0003846  0.0050615  0.0130586
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -2.317e-01  4.945e-02  -4.685 7.10e-05 ***
## `I rates`         7.286e-01  1.816e-01   4.011 0.000430 ***
## `NII volatility`  1.399e-03  2.093e-03   0.669 0.509404
## ROA               7.249e+00  8.964e-01   8.087 1.09e-08 ***
## Leverage          1.698e-02  4.437e-03   3.827 0.000698 ***
## `Inflation rate`  5.716e-01  4.565e-01   1.252 0.221225
## `OAS MBS spread`  5.878e-05  9.781e-05   0.601 0.552862
## COVID_dummy       2.071e-02  5.467e-03   3.787 0.000775 ***
## post_dummy        3.649e-03  7.810e-03   0.467 0.644145
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.008116 on 27 degrees of freedom
## Multiple R-squared:  0.9381,Adjusted R-squared:  0.9197
## F-statistic: 51.13 on 8 and 27 DF,  p-value: 2.532e-14
## OK: residuals appear as normally distributed (p = 0.786).
## OK: Error variance appears to be homoscedastic (p = 0.275).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.571179         1.265764         2.826356         1.464139
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.539165         1.439574         2.559185         2.547144
##
##  studentized Breusch-Pagan test
##
## data:  stanley1_reg
## BP = 9.7447, df = 8, p-value = 0.2834
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = state1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.02689 -0.01575 -0.00048  0.01036  0.03468
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.1736858  0.0802285   2.165 0.039402 *
## `I rates`         2.5894115  0.5688208   4.552 0.000101 ***
## `NII volatility` -0.0120255  0.0107716  -1.116 0.274087
## ROA               7.5384678  6.5547108   1.150 0.260194
```

```
## Leverage         -0.0113510  0.0037318  -3.042 0.005186 **
## `Inflation rate`  0.2740942  1.0778026   0.254 0.801184
## `OAS MBS spread` -0.0001321  0.0002449  -0.539 0.594040
## COVID_dummy       0.0579443  0.0100604   5.760 3.99e-06 ***
## post_dummy        0.0646533  0.0172357   3.751 0.000852 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01987 on 27 degrees of freedom
## Multiple R-squared:  0.843,Adjusted R-squared:  0.7965
## F-statistic: 18.12 on 8 and 27 DF,  p-value: 5.363e-09
## OK: residuals appear as normally distributed (p = 0.076).
## OK: Error variance appears to be homoscedastic (p = 0.611).
##        `I rates` `NII volatility`              ROA         Leverage
##         2.570993         1.370464         2.756946         2.069871
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.362193         1.506135         1.445945         2.069767
##
##  studentized Breusch-Pagan test
##
## data:  state1_reg
## BP = 11.126, df = 8, p-value = 0.1947
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = truist1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.074676 -0.005169  0.000484  0.009589  0.041719
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.1361535  0.1005195   1.354   0.1868
## `I rates`        -0.5143712  0.6105844  -0.842   0.4070
## `NII volatility`  0.0020574  0.0225446   0.091   0.9280
## ROA              23.2221522 11.5437198   2.012   0.0543 .
## Leverage         -0.0230269  0.0227803  -1.011   0.3211
## `Inflation rate` -1.4503626  1.3196320  -1.099   0.2814
## `OAS MBS spread` -0.0001063  0.0003330  -0.319   0.7520
## COVID_dummy      -0.0795170  0.0154713  -5.140 2.09e-05 ***
## post_dummy        0.0625394  0.0279525   2.237   0.0337 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.02376 on 27 degrees of freedom
## Multiple R-squared:  0.7696,Adjusted R-squared:  0.7014
## F-statistic: 11.28 on 8 and 27 DF,  p-value: 7.403e-07
## Warning: Non-normality of residuals detected (p < .001).
## OK: Error variance appears to be homoscedastic (p = 0.982).
##         `I rates` `NII volatility`              ROA         Leverage
##          2.070580         3.631547         2.102571         3.586631
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##          2.475103         1.946517         2.390144         3.804980
##
##  studentized Breusch-Pagan test
##
## data:  truist1_reg
## BP = 12.813, df = 8, p-value = 0.1184
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = bancorp1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.054199 -0.004797  0.001435  0.005969  0.018829
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.761e-01  1.131e-01   1.557  0.13114
## `I rates`        -1.178e+00  4.073e-01  -2.892  0.00747 **
## `NII volatility`  4.927e-01  8.533e-02   5.774 3.84e-06 ***
## ROA               5.594e+00  3.588e+00   1.559  0.13062
## Leverage         -1.698e-02  8.218e-03  -2.066  0.04857 *
## `Inflation rate` -8.342e-01  8.646e-01  -0.965  0.34317
## `OAS MBS spread` -2.191e-05  2.237e-04  -0.098  0.92269
## COVID_dummy      -3.848e-02  1.483e-02  -2.596  0.01508 *
## post_dummy        4.242e-02  1.877e-02   2.260  0.03207 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01519 on 27 degrees of freedom
## Multiple R-squared:  0.9104,Adjusted R-squared:  0.8839
## F-statistic: 34.29 on 8 and 27 DF,  p-value: 3.416e-12
## Warning: Non-normality of residuals detected (p < .001).
## OK: Error variance appears to be homoscedastic (p = 0.275).
##         `I rates` `NII volatility`              ROA         Leverage
##          2.254303         5.981244         6.311464        11.751048
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
```

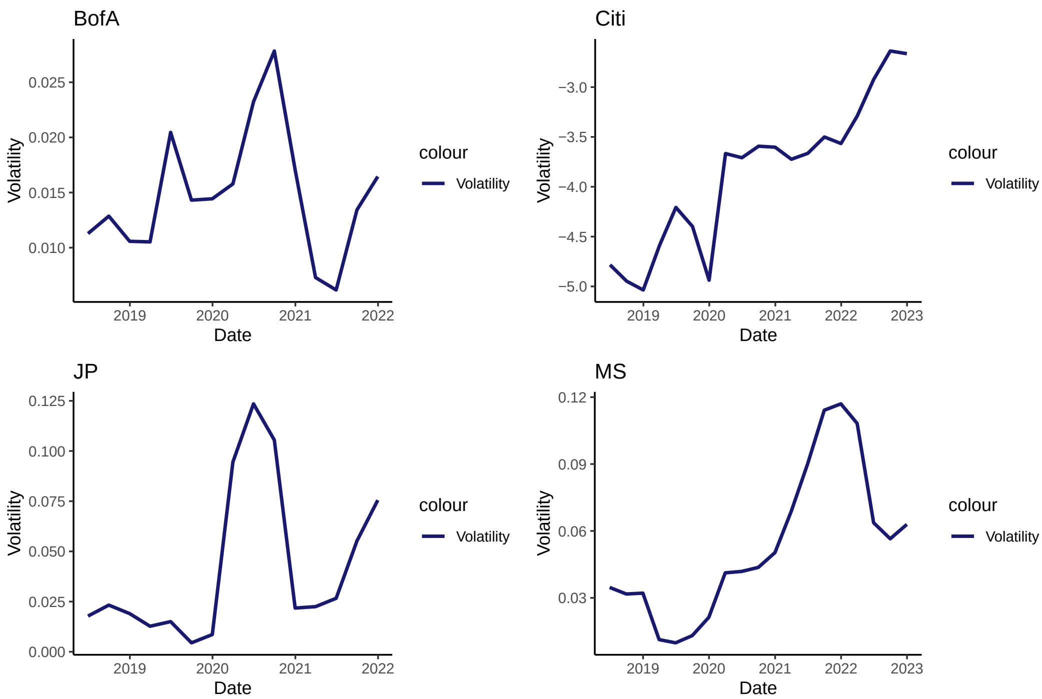
```
##         2.599551         2.148783         5.369845         4.197049
##
##  studentized Breusch-Pagan test
##
## data:  bancorp1_reg
## BP = 12.513, df = 8, p-value = 0.1297
```

```
##
## Call:
## lm(formula = HTM ~ `I rates` + `NII volatility` + ROA + Leverage +
##     `Inflation rate` + `OAS MBS spread` + COVID_dummy + post_dummy,
##     data = wells1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0227935 -0.0098156  0.0008906  0.0070572  0.0237762
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.1269134  0.0900953  -1.409 0.170349
## `I rates`         0.7565670  0.3181144   2.378 0.024730 *
## `NII volatility` -0.0068694  0.0292388  -0.235 0.816026
## ROA              -5.3892677  1.6342946  -3.298 0.002737 **
## Leverage          0.0271110  0.0083218   3.258 0.003026 **
## `Inflation rate`  3.1074021  0.7315654   4.248 0.000229 ***
## `OAS MBS spread` -0.0006825  0.0001764  -3.869 0.000626 ***
## COVID_dummy      -0.0200324  0.0139639  -1.435 0.162888
## post_dummy        0.0104106  0.0144613   0.720 0.477776
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01304 on 27 degrees of freedom
## Multiple R-squared:  0.9217,Adjusted R-squared:  0.8985
## F-statistic: 39.74 on 8 and 27 DF,  p-value: 5.706e-13
## OK: residuals appear as normally distributed (p = 0.784).
## OK: Error variance appears to be homoscedastic (p = 0.613).
##        `I rates` `NII volatility`              ROA         Leverage
##         1.866891         2.890835         6.826394         5.587963
## `Inflation rate` `OAS MBS spread`      COVID_dummy       post_dummy
##         2.526653         1.814194         6.467522         3.382813
##
##  studentized Breusch-Pagan test
##
## data:  wells1_reg
## BP = 13.075, df = 8, p-value = 0.1093
```

Appendix E

Volatility Analysis

E.1 Volatility plots



E.2 Regressions

```
##
## Call:
## lm(formula = Volatility ~ HTM + Deposits + LCR + ROE + `Loan risk` +
##     `Loan growth` + dummy, data = bofa1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0041067 -0.0010404  0.0001423  0.0012563  0.0026861
```

```
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -0.041622   0.051663  -0.806  0.44694
## HTM           -0.152764   0.033949  -4.500  0.00280 **
## Deposits       0.237698   0.061400   3.871  0.00612 **
## LCR            0.010848   0.035577   0.305  0.76929
## ROE           -0.016396   0.030429  -0.539  0.60670
## `Loan risk`   -0.108325   0.032555  -3.327  0.01263 *
## `Loan growth`  0.064034   0.021672   2.955  0.02127 *
## dummy          0.009727   0.003507   2.774  0.02755 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.002692 on 7 degrees of freedom
## Multiple R-squared:  0.8914,Adjusted R-squared:  0.7829
## F-statistic:  8.21 on 7 and 7 DF,  p-value: 0.006305
## OK: residuals appear as normally distributed (p = 0.394).
## OK: Error variance appears to be homoscedastic (p = 0.317).
##           HTM      Deposits           LCR           ROE   `Loan risk`
##      7.212325      6.004516      1.881921      1.816491      1.866954
## `Loan growth`         dummy
##      3.331563      2.942222
##
##  studentized Breusch-Pagan test
##
## data:  bofa1_reg
## BP = 4.6692, df = 7, p-value = 0.7003
```

```
##
## Call:
## lm(formula = Volatility ~ HTM + LCR + ROE + `Loan risk` + `AFS risk` +
##     Deposits + dummy, data = citi1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.41025 -0.04671 -0.00969  0.10147  0.24896
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.03556    1.33462   0.027 0.979222
## HTM          0.53948    0.30092   1.793 0.100519
## LCR          2.75469    3.03661   0.907 0.383764
## ROE         -9.38906    2.04192  -4.598 0.000767 ***
## `Loan risk`  2.29067    2.12124   1.080 0.303307
## `AFS risk`  12.60524    2.69764   4.673 0.000680 ***
## Deposits     0.94156    3.03177   0.311 0.761938
```

```
## dummy       -0.34613    0.22152  -1.563 0.146459
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2079 on 11 degrees of freedom
## Multiple R-squared:  0.953,Adjusted R-squared:  0.9231
## F-statistic: 31.86 on 7 and 11 DF,  p-value: 1.895e-06
## OK: residuals appear as normally distributed (p = 0.386).
## OK: Error variance appears to be homoscedastic (p = 0.365).
##         HTM         LCR         ROE `Loan risk`  `AFS risk`    Deposits
##   10.024182    1.449411    1.437566    1.823280    6.111706    4.882819
##       dummy
##    2.867042
##
##  studentized Breusch-Pagan test
##
## data:  citi1_reg
## BP = 4.9097, df = 7, p-value = 0.671
```

```
##
## Call:
## lm(formula = Volatility ~ HTM + Deposits + LCR + ROE + `Loan risk` +
##     dummy, data = jpmorgan1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.022772 -0.008091 -0.001724  0.007019  0.022167
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.40315    0.63912  -3.760  0.00554 **
## HTM          0.51506    0.51557   0.999  0.34704
## Deposits     1.39813    0.46799   2.988  0.01740 *
## LCR          0.49281    0.33817   1.457  0.18315
## ROE         -0.45007    0.14227  -3.164  0.01332 *
## `Loan risk`  1.48097    0.54744   2.705  0.02685 *
## dummy        0.02317    0.02132   1.087  0.30885
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01718 on 8 degrees of freedom
## Multiple R-squared:  0.8893,Adjusted R-squared:  0.8063
## F-statistic: 10.72 on 6 and 8 DF,  p-value: 0.00187
## OK: residuals appear as normally distributed (p = 0.785).
## OK: Error variance appears to be homoscedastic (p = 0.736).
##         HTM    Deposits         LCR         ROE `Loan risk`       dummy
##   13.658130   14.028777    2.702808    1.899326   11.832437    2.669811
```

```
##
##  studentized Breusch-Pagan test
##
## data:  jpmorgan1_reg
## BP = 5.1975, df = 6, p-value = 0.5187
```

```
##
## Call:
## lm(formula = Volatility ~ HTM + LCR + ROE + Deposits + AFS +
##     `Loan risk` + dummy, data = stanley1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.37675 -0.11845 -0.03024  0.10817  0.34759
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.62778    1.69614  -0.370 0.718317
## HTM         -1.59106    0.49544  -3.211 0.008285 **
## LCR         -2.90540    1.21562  -2.390 0.035858 *
## ROE          0.07613    0.11640   0.654 0.526536
## Deposits     5.04215    0.89611   5.627 0.000154 ***
## AFS         56.34420   28.21272   1.997 0.071154 .
## `Loan risk` -0.78023    0.71332  -1.094 0.297419
## dummy        0.49192    0.18382   2.676 0.021555 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2264 on 11 degrees of freedom
## Multiple R-squared:  0.944,Adjusted R-squared:  0.9083
## F-statistic: 26.48 on 7 and 11 DF,  p-value: 4.872e-06
## OK: residuals appear as normally distributed (p = 0.807).
## OK: Error variance appears to be homoscedastic (p = 0.443).
##         HTM         LCR         ROE    Deposits         AFS `Loan risk`
##    7.423574    1.916896    1.298227    7.342820    1.501779    4.265065
##       dummy
##    1.665678
##
##  studentized Breusch-Pagan test
##
## data:  stanley1_reg
## BP = 9.382, df = 7, p-value = 0.2264
```

E.3 Loan risk exposure trends

Table E.1: JPMorgan loan exposure

Date	BHCKS417	BHCKS441	BHCKS443	BHCKH178	BHCKH182	BHCKS462	BHCKS447	BHCKS463
12/31/2020	$261,400	$123,558,500	$110,200	$28,221,000	$168,000	$2,541,000	$168,000	$2,541,000
9/30/2020	$292,000	$129,481,500	$92,400	$27,066,000	$168,000	$2,436,000	$168,000	$2,436,000
6/30/2020	$294,000	$131,529,500	$32,600	$30,782,000	$204,000	$2,656,500	$204,000	$2,656,500
3/31/2020	$369,600	$133,521,000	$22,600	$32,228,000	$637,500	$2,755,500	$637,500	$2,755,500
12/31/2019	$581,800	$132,002,000	$27,800	$35,077,000	$583,500	$3,771,000	$583,500	$3,771,000
9/30/2019	$945,200	$135,091,500	$31,800	$36,416,000	$847,500	$2,452,500	$847,500	$2,452,500
6/30/2019	$206,000	$140,588,000	$867,200	$38,106,000	$525,000	$2,446,500	$525,000	$2,446,500
3/31/2019	$17,200	$141,840,000	$1,144,800	$39,491,000	$892,500	$3,999,000	$892,500	$3,999,000
12/31/2018	$18,800	$145,553,500	$1,399,800	$40,940,000	$1,084,500	$3,646,500	$1,084,500	$3,646,500
9/30/2018	$20,600	$148,109,000	$1,445,000	$43,306,000	$1,482,000	$3,433,500	$1,482,000	$3,433,500
6/30/2018	$22,000	$144,712,000	$1,636,800	$45,212,000	$2,712,000	$3,921,000	$2,712,000	$3,921,000
3/31/2018	$23,800	$140,391,500	$1,735,000	$48,887,000	$2,989,500	$3,786,000	$2,989,500	$3,786,000

Table E.2: BofA loan exposure

Date	BHCKS416	BHCKS415	BHCKS417	BHCKS437	BHCKS441	BHCKS443	BHCKS447	BHCKS460	BHCKS463	BHCKS462
3/31/2021	$530,000	$7,600	$25,000	$3,000	$2,577,800	$35,986,000	$510,000	$3,748,600	$4,665,000	$536,590,000
12/31/2020	$386,000	$11,400	$31,000	$12,000	$2,538,400	$37,634,000	$516,000	$3,875,400	$4,485,000	$551,295,000
9/30/2020	$296,000	$13,600	$42,000	$1,500	$2,513,200	$39,877,000	$523,500	$3,873,400	$5,688,000	$568,272,000
6/30/2020	$865,000	$10,600	$20,000	$1,500	$2,511,800	$40,072,000	$510,000	$4,199,200	$6,877,500	$600,644,000
3/31/2020	$865,500	$17,400	$89,000	$12,000	$3,986,200	$42,510,000	$627,000	$4,710,400	$5,316,000	$673,078,000
12/31/2019	$929,000	$30,200	$86,000	$7,500	$3,994,800	$43,214,000	$642,000	$4,552,200	$5,233,500	$619,155,000
9/30/2019	$698,000	$28,600	$65,000	$7,500	$4,021,000	$43,396,000	$859,500	$4,310,200	$6,192,000	$617,552,000
6/30/2019	$577,500	$21,000	$52,000	$9,000	$4,161,000	$45,920,000	$927,000	$4,473,600	$5,386,500	$613,625,000
3/31/2019	$431,000	$12,800	$56,000	$9,000	$4,244,000	$47,854,000	$948,000	$4,538,200	$4,173,000	$608,847,000
12/31/2018	$588,500	$10,200	$35,000	$9,000	$4,398,600	$49,574,000	$2,394,000	$4,506,800	$4,452,000	$608,277,000
9/30/2018	$602,000	$11,800	$34,000	$25,500	$4,559,000	$54,581,000	$3,060,000	$4,349,400	$4,879,500	$595,139,000
6/30/2018	$526,500	$13,000	$34,000	$42,000	$4,828,600	$58,186,000	$3,417,000	$4,187,000	$5,482,500	$596,142,000
3/31/2018	$994,500	$10,800	$984,000	$4,500	$5,179,600	$60,086,000	$3,667,500	$4,364,800	$6,022,500	$589,617,000

Table E.4: Morgan Stanley loan exposure

Date	BHCKS416	BHCKS417	BHCKS429	BHCKS434	BHCKS436	BHCKS443	BHCKS461	BHCKS460	BHCKS462
6/30/2022	$508,500	$654,000	$948,000	$27,000	$10,860,000	$164,000	$4,000	$194,800	$38,755,000
3/31/2022	$920,000	$1,133,000	$1,224,000	$27,000	$10,611,000	$171,000	$5,500	$180,400	$38,587,000
12/31/2021	$1,347,000	$1,009,000	$2,548,500	$38,000	$9,206,000	$199,000	$5,500	$177,000	$36,578,000
9/30/2021	$322,500	$2,467,000	$2,640,000	$27,000	$8,968,000	$211,000	$4,000	$170,200	$37,541,000
6/30/2021	$256,000	$1,424,000	$2,758,500	$27,000	$9,494,000	$236,000	$16,500	$169,000	$38,428,000
3/31/2021	$385,000	$1,775,000	$1,108,500	$27,000	$9,230,000	$531,000	$19,000	$199,200	$38,839,000
12/31/2020	$290,500	$1,564,000	$1,134,000	$66,800	$10,593,000	$6,478,000	$29,000	$301,800	$39,655,000
9/30/2020	$67,000	$691,000	$1,032,000	$66,800	$11,189,000	$6,268,000	$30,000	$299,800	$39,079,000
6/30/2020	$109,500	$774,000	$1,270,500	$66,800	$13,148,000	$5,786,000	$40,000	$278,600	$42,518,000
3/31/2020	$183,000	$787,000	$714,000	$65,800	$15,363,000	$5,380,000	$37,500	$247,200	$48,819,000
12/31/2019	$173,000	$823,000	$709,500	$66,800	$12,100,000	$153,000	$40,000	$200,600	$37,729,000
9/30/2019	$268,500	$549,000	$768,000	$66,800	$10,198,000	$160,000	$40,000	$200,800	$34,447,000
6/30/2019	$258,500	$734,000	$903,000	$66,800	$11,740,000	$149,000	$46,000	$238,400	$31,048,000
3/31/2019	$285,000	$708,000	$1,084,500	$66,800	$12,656,000	$141,000	$48,000	$261,600	$29,901,000
12/31/2018	$219,000	$711,000	$792,000	$65,600	$13,288,000	$142,000	$47,000	$253,000	$29,968,000
9/30/2018	$131,000	$654,000	$975,000	$66,800	$11,100,000	$131,000	$31,500	$244,600	$29,628,000
6/30/2018	$169,500	$1,000,000	$1,032,000	$66,600	$13,415,000	$116,000	$-	$131,600	$29,308,000
3/31/2018	$13,000	$665,000	$1,059,000	$66,000	$11,767,000	$119,000	$-	$203,200	$29,431,000

Appendix F

Liquidity Analysis

F.1 Regressions

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy, data = TradVol)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.03464 -0.31865 -0.05602  0.48107  0.84780
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    20.7345     3.0813   6.729 2.11e-05 ***
## HTM           -52.1703    12.4183  -4.201  0.00123 **
## `Term spread` 171.5530   100.7544   1.703  0.11436
## `S&P 500`      -0.5771     2.4953  -0.231  0.82100
## VIX            -0.2933     1.0311  -0.284  0.78092
## OAS            -0.2376     0.5596  -0.424  0.67871
## COVID_dummy    -0.3850     0.6884  -0.559  0.58627
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6604 on 12 degrees of freedom
## Multiple R-squared:  0.8265,Adjusted R-squared:  0.7397
## F-statistic: 9.525 on 6 and 12 DF,  p-value: 0.0005545
## OK: residuals appear as normally distributed (p = 0.600).
## OK: Error variance appears to be homoscedastic (p = 0.261).
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      4.764778      6.259746      2.460897      3.765128      4.524651
##   COVID_dummy
##      4.804589
##
##  studentized Breusch-Pagan test
```

```
##
## data:  TradVol_reg
## BP = 7.4278, df = 6, p-value = 0.2831
```

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy + post_dummy, data = TradVol)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.02247 -0.31464 -0.02836  0.42751  0.84661
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    21.3712     3.2574   6.561 4.07e-05 ***
## HTM           -58.2630    15.1094  -3.856  0.00267 **
## `Term spread` 199.2505   109.3450   1.822  0.09570 .
## `S&P 500`      -0.3794     2.5579  -0.148  0.88478
## VIX            -0.4451     1.0710  -0.416  0.68571
## OAS            -0.2575     0.5712  -0.451  0.66088
## COVID_dummy    -0.3165     0.7080  -0.447  0.66350
## post_dummy      0.5644     0.7640   0.739  0.47551
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6733 on 11 degrees of freedom
## Multiple R-squared:  0.8347,Adjusted R-squared:  0.7295
## F-statistic: 7.933 on 7 and 11 DF,  p-value: 0.001454
## OK: residuals appear as normally distributed (p = 0.572).
## OK: Error variance appears to be homoscedastic (p = 0.161).
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      6.786627      7.093645      2.488136      3.909037      4.534764
##   COVID_dummy    post_dummy
##      4.888468      3.252818
##
##  studentized Breusch-Pagan test
##
## data:  TradVol_reg
## BP = 8.3236, df = 7, p-value = 0.3049
```

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy, data = NumberTrade)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.65892 -0.08919 -0.05336  0.23005  0.66040
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)     5.9013     1.7781   3.319 0.006123 **
## HTM            -1.6786     0.3386  -4.957 0.000332 ***
## `Term spread`   0.2484     0.2328   1.067 0.306884
## `S&P 500`      -0.0971     0.1083  -0.897 0.387460
## VIX             0.7246     1.3970   0.519 0.613411
## OAS            -1.3637     0.8122  -1.679 0.118965
## COVID_dummy    -0.4821     0.3200  -1.507 0.157731
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3743 on 12 degrees of freedom
## Multiple R-squared:  0.8073,Adjusted R-squared:  0.711
## F-statistic: 8.379 on 6 and 12 DF,  p-value: 0.0009996
## OK: residuals appear as normally distributed (p = 0.523).
## OK: Error variance appears to be homoscedastic (p = 0.138).
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      3.340907      3.688171      1.622568      2.274787      2.580215
##   COVID_dummy
##      3.230384
##
##  studentized Breusch-Pagan test
##
## data:  NumberTrade_reg
## BP = 12.041, df = 6, p-value = 0.06106
```

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy + post_dummy, data = NumberTrade)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.65893 -0.14677 -0.07577  0.22591  0.63771
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6.32937    1.91406   3.307 0.006993 **
## HTM           -1.84071    0.41467  -4.439 0.000997 ***
## `Term spread`  0.32137    0.25910   1.240 0.240657
## `S&P 500`     -0.05797    0.12363  -0.469 0.648299
## VIX            0.32092    1.53649   0.209 0.838372
```

```
## OAS           -1.35990    0.82958  -1.639 0.129418
## COVID_dummy   -0.43699    0.33298  -1.312 0.216122
## post_dummy     0.32905    0.46445   0.708 0.493385
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3823 on 11 degrees of freedom
## Multiple R-squared:  0.8157,Adjusted R-squared:  0.6985
## F-statistic: 6.956 on 7 and 11 DF,  p-value: 0.00252
## OK: residuals appear as normally distributed (p = 0.871).
## OK: Error variance appears to be homoscedastic (p = 0.143).
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      4.802382      4.380078      2.027351      2.637507      2.580323
##   COVID_dummy    post_dummy
##      3.353149      3.727835
##
##  studentized Breusch-Pagan test
##
## data:  NumberTrade_reg
## BP = 10.9, df = 7, p-value = 0.1431
```

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy, data = TradVol)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.84298 -0.62124 -0.07576  0.59197  2.15962
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    19.7766     7.4777   2.645   0.0214 *
## HTM            -0.9250     2.0303  -0.456   0.6568
## `Term spread`  -0.2499     0.6316  -0.396   0.6993
## `S&P 500`       0.1160     0.3004   0.386   0.7062
## VIX            -2.8401     1.1556  -2.458   0.0302 *
## OAS             0.4796     0.6294   0.762   0.4607
## COVID_dummy     0.6601     1.3291   0.497   0.6284
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.121 on 12 degrees of freedom
## Multiple R-squared:  0.5003,Adjusted R-squared:  0.2504
## F-statistic: 2.002 on 6 and 12 DF,  p-value: 0.1442
## OK: residuals appear as normally distributed (p = 0.950).
## OK: Error variance appears to be homoscedastic (p = 0.561).
```

```
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      3.887976      3.044697      1.505697      1.806868      2.135449
##   COVID_dummy
##      6.218743
##
##  studentized Breusch-Pagan test
##
## data:  TradVol_reg
## BP = 5.6144, df = 6, p-value = 0.4677
```

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy + post_dummy, data = TradVol)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.66781 -0.40872 -0.08951  0.64744  1.28690
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   18.25276    7.21465   2.530    0.028 *
## HTM           -0.09479    2.01910  -0.047    0.963
## `Term spread` -0.35656    0.60738  -0.587    0.569
## `S&P 500`     -0.13794    0.33484  -0.412    0.688
## VIX           -1.73839    1.33366  -1.303    0.219
## OAS            0.27486    0.61685   0.446    0.665
## COVID_dummy    0.57903    1.27024   0.456    0.657
## post_dummy    -1.67515    1.13911  -1.471    0.169
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.07 on 11 degrees of freedom
## Multiple R-squared:  0.5824,Adjusted R-squared:  0.3166
## F-statistic: 2.191 on 7 and 11 DF,  p-value: 0.1179
## OK: residuals appear as normally distributed (p = 0.785).
## OK: Error variance appears to be homoscedastic (p = 0.346).
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      4.217697      3.088782      2.051290      2.639851      2.250105
##   COVID_dummy    post_dummy
##      6.230480      2.863119
##
##  studentized Breusch-Pagan test
##
## data:  TradVol_reg
## BP = 9.5872, df = 7, p-value = 0.2132
```

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy, data = NumberTrade)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.9249 -0.3723 -0.0422  0.3306  1.2704
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   11.83437    4.33118   2.732   0.0182 *
## HTM            0.45958    1.17598   0.391   0.7028
## `Term spread` -0.23131    0.36581  -0.632   0.5390
## `S&P 500`      0.08395    0.17402   0.482   0.6382
## VIX           -1.28755    0.66932  -1.924   0.0784 .
## OAS            0.21158    0.36454   0.580   0.5724
## COVID_dummy    0.21501    0.76983   0.279   0.7848
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6491 on 12 degrees of freedom
## Multiple R-squared:  0.4206,Adjusted R-squared:  0.1309
## F-statistic: 1.452 on 6 and 12 DF,  p-value: 0.2738
## OK: residuals appear as normally distributed (p = 0.944).
## OK: Error variance appears to be homoscedastic (p = 0.267).
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      3.887976      3.044697      1.505697      1.806868      2.135449
##   COVID_dummy
##      6.218743
##
##  studentized Breusch-Pagan test
##
## data:  NumberTrade_reg
## BP = 4.9061, df = 6, p-value = 0.5559
```

```
##
## Call:
## lm(formula = UMBS ~ HTM + `Term spread` + `S&P 500` + VIX + OAS +
##     COVID_dummy + post_dummy, data = NumberTrade)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.89496 -0.27031  0.03394  0.35576  0.77849
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)   10.97541    4.20047   2.613   0.0241 *
## HTM            0.92755    1.17555   0.789   0.4468
## `Term spread` -0.29146    0.35363  -0.824   0.4273
## `S&P 500`     -0.05920    0.19495  -0.304   0.7671
## VIX           -0.66653    0.77648  -0.858   0.4090
## OAS            0.09615    0.35914   0.268   0.7939
## COVID_dummy    0.16930    0.73955   0.229   0.8231
## post_dummy    -0.94426    0.66320  -1.424   0.1822
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.623 on 11 degrees of freedom
## Multiple R-squared:  0.5108,Adjusted R-squared:  0.1994
## F-statistic: 1.641 on 7 and 11 DF,  p-value: 0.2222
## OK: residuals appear as normally distributed (p = 0.953).
## Warning: Heteroscedasticity (non-constant error variance) detected (p = 0.045).
##           HTM `Term spread`     `S&P 500`           VIX           OAS
##      4.217697      3.088782      2.051290      2.639851      2.250105
##   COVID_dummy    post_dummy
##      6.230480      2.863119
##
##  studentized Breusch-Pagan test
##
## data:  NumberTrade_reg
## BP = 11.623, df = 7, p-value = 0.1137
```

```
##
## Call:
## lm(formula = `Trading Revenues` ~ UMBS + `Term spread` + `S&P 500` +
##     VIX + OAS + COVID_dummy, data = Revenues)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2475483 -1466211  -292238  1139598  2948799
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.274e+07  4.584e+06   2.779   0.0240 *
## UMBS          -3.952e+02  1.335e+02  -2.960   0.0182 *
## `Term spread`  2.544e+08  3.190e+08   0.798   0.4482
## `S&P 500`     -1.216e+07  6.330e+06  -1.921   0.0910 .
## VIX           -9.460e+04  1.533e+05  -0.617   0.5543
## OAS            4.758e+04  4.569e+04   1.041   0.3282
## COVID_dummy   -3.539e+06  2.713e+06  -1.305   0.2283
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 2218000 on 8 degrees of freedom
## Multiple R-squared:  0.7629,Adjusted R-squared:  0.5851
## F-statistic:  4.29 on 6 and 8 DF,  p-value: 0.0312
## OK: residuals appear as normally distributed (p = 0.326).
## OK: Error variance appears to be homoscedastic (p = 0.650).
##          UMBS `Term spread`     `S&P 500`           VIX           OAS
##      1.947673      5.286523      1.973282      3.425176      3.546891
##   COVID_dummy
##      5.586775
##
##  studentized Breusch-Pagan test
##
## data:  Revenues_reg
## BP = 5.0996, df = 6, p-value = 0.5311
```

```
##
## Call:
## lm(formula = `Trading Revenues` ~ UMBS + `Term spread` + `S&P 500` +
##     VIX + OAS + COVID_dummy + post_dummy, data = Revenues)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2449968 -1248218   235100   996753  3324310
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.465e+07  4.193e+06   3.494  0.00503 **
## UMBS          -4.001e+02  1.198e+02  -3.340  0.00660 **
## `Term spread`  7.810e+07  2.824e+08   0.277  0.78726
## `S&P 500`     -1.303e+07  5.929e+06  -2.197  0.05033 .
## VIX           -1.131e+05  1.380e+05  -0.820  0.42989
## OAS            2.469e+04  3.823e+04   0.646  0.53166
## COVID_dummy   -2.255e+06  2.424e+06  -0.930  0.37222
## post_dummy    -7.657e+06  2.094e+06  -3.656  0.00378 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2155000 on 11 degrees of freedom
## Multiple R-squared:  0.7797,Adjusted R-squared:  0.6395
## F-statistic: 5.561 on 7 and 11 DF,  p-value: 0.006146
## OK: residuals appear as normally distributed (p = 0.553).
## OK: Error variance appears to be homoscedastic (p = 0.517).
##          UMBS `Term spread`     `S&P 500`           VIX           OAS
##      1.912710      4.685327      1.965458      3.341783      2.928887
##   COVID_dummy    post_dummy
##      5.593382      2.386164
##
```

```
##  studentized Breusch-Pagan test
##
## data:  Revenues_reg
## BP = 5.5368, df = 7, p-value = 0.5947
```

F.2 Daily trading data

12/1/2022				COUPON			
UMBS[1]	<= 3.0	3.50	4.00	4.50	5.00	5.50	> 5.5
AVERAGE PRICE	86.40	92.10	94.50	96.10	99.60	100.90	99.70
WEIGHTED AVG. PRICE	83.80	92.50	95.70	97.70	100.60	102.00	102.90
AVG. PRICE BOTTOM 5 TRADES	77.50	84.60	76.90	75.80	94.80	97.00	84.20
2ND QUARTILE PRICE	85.40	92.10	94.90	97.40	99.70	101.00	97.70
3RD QUARTILE PRICE	86.10	92.10	95.10	97.40	100.00	101.30	102.80
4TH QUARTILE PRICE	88.70	92.60	95.70	97.90	100.40	102.00	103.40
AVG. PRICE TOP 5 TRADES	93.00	95.00	98.20	99.80	101.10	103.00	105.50
STANDARD DEVIATION	2.70	1.70	3.60	5.10	1.50	2.00	6.40
VOLUME OF TRADES (000'S)	6751422.80	1929012.30	559503.20	5568487.60	1004093.80	595902.90	573438.50
NUMBER OF TRADES	918.00	319.00	328.00	326.00	150.00	130.00	138.00

[1] UMBS gathers al in one Finnie-Mae and Freddie-Mac. However UMBS categorization has been used from mid 2019 to 2022. When UMBS does not apply I used FNMA andFHLMC

	COUPON					
FNMA	<= 3.0	3.50	4.00	4.50	5.00	5.50
AVERAGE PRICE	*	*	*	92.20	*	*
WEIGHTED AVG. PRICE	*	*	*	92.10	*	*
AVG. PRICE BOTTOM 5 TRADES	*	*	*	92.20	*	*
2ND QUARTILE PRICE	*	*	*	*	*	*
3RD QUARTILE PRICE	*	*	*	*	*	*
4TH QUARTILE PRICE	*	*	*	*	*	*
AVG. PRICE TOP 5 TRADES	*	*	*	92.20	*	*
STANDARD DEVIATION	*	*	*	1.00	*	*
VOLUME OF TRADES (000'S)	*	*	*	25600.00	*	*
NUMBER OF TRADES	*	*	*	5.00	*	*

	COUPON					
FHLMC	<= 3.0	3.50	4.00	4.50	5.00	5.50
AVERAGE PRICE	88.10	91.80	95.10	96.00	98.00	*
WEIGHTED AVG. PRICE	87.30	88.60	98.40	98.60	102.10	*
AVG. PRICE BOTTOM 5 TRADES	79.30	86.50	90.20	91.10	98.00	*
2ND QUARTILE PRICE	87.70	92.10	95.00	95.00	*	*
3RD QUARTILE PRICE	89.20	92.10	95.00	97.40	*	*
4TH QUARTILE PRICE	89.80	94.00	95.70	97.90	*	*
AVG. PRICE TOP 5 TRADES	93.70	94.70	96.70	98.70	98.00	*
STANDARD DEVIATION	3.80	2.70	2.10	3.20	2.20	*
VOLUME OF TRADES (000'S)	19902.30	14376.00	21070.30	170.90	6820.70	*
NUMBER OF TRADES	67.00	60.00	66.00	54.00	6.00	*

	COUPON					
GNMA	<= 3.0	3.50	4.00	4.50	5.00	5.50
AVERAGE PRICE	89.30	93.70	95.50	97.90	99.80	101.10
WEIGHTED AVG. PRICE	88.90	94.60	95.40	98.20	100.30	101.40
AVG. PRICE BOTTOM 5 TRADES	84.80	89.40	93.30	96.50	91.10	97.30
2ND QUARTILE PRICE	88.10	93.00	95.20	97.50	99.80	100.60
3RD QUARTILE PRICE	88.60	93.50	95.80	98.20	100.20	101.40
4TH QUARTILE PRICE	90.90	94.80	96.00	98.40	101.00	102.00
AVG. PRICE TOP 5 TRADES	94.20	96.50	97.40	98.80	102.80	103.30
STANDARD DEVIATION	2.60	2.10	1.50	0.80	2.60	1.50
VOLUME OF TRADES (000'S)	207361.50	730495.80	124615.90	329565.10	765688.10	1010334.50
NUMBER OF TRADES	84.00	43.00	30.00	50.00	89.00	88.00