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Regulatory Aftermath & Safeguards: Shadow Banking Risks in the Mortgage Origination Market

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Abstract
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Keywords
mortgage, shadow bank, bank, regulation, mortgage origination, dodd-frank act, fannie mae, interest rate, risk, safeguard

Disciplines
Finance and Financial Management

REGULATORY AFTERMATH & SAFEGUARDS: SHADOW BANKING RISKS IN THE MORTGAGE ORIGINATION MARKET

By

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ABSTRACT

In response to the subprime mortgage crisis and increased regulatory protectionism, shadow banks have significantly increased market share in the mortgage origination market, originating over 50 percent of conforming loans. This paper explores the effect of an inevitable interest rate increase on a potential deterioration in loan quality. Using 14.8 million loans from the Fannie Mae Single-Family Loan Acquisition dataset, this study generates a scenario analysis of mortgage origination based on parallel yield curve shifts to better understand the strength of traditional and shadow banks and their ability to withstand the pressure of rising interest rate. A secondary analysis examines the loan performance under stress conditions similar to the recent financial crisis. The results demonstrate higher shadow bank sensitivity to interest rate changes and a higher risk premium for subprime mortgages among banks. The findings substantiate the strength of the conforming loan standards as safeguards to ensure minimum loan quality.

Keywords: Mortgage, Shadow Bank, Bank, Regulation, Mortgage Origination

1. INTRODUCTION

The residential mortgage market underwent fundamental changes in the last decade. Janet Yellen and Ben Bernanke cite the loose mortgage lending standards and the subsequent significant losses in residential mortgage loans to subprime borrowers as “the most prominent triggers” of the recession (Bernanke 2010). The run and collapse of the subprime loan market and the increased regulatory protectionism revamped the landscape of the mortgage origination and underwriting market. The recent regulation was intended to promote safer lending standards among financial institutions, but it also promoted foundational changes to the market. Traditional banks have retreated from the market, with non-banks increasing market share, particularly in subprime loans.[1] The presence of shadow banks has filled an important gap by providing access to credit and homeownership to individuals. The significantly different business models and funding structures of traditional and shadow banks pose new risks and market vulnerabilities. The increasing interest rate environment will pressure the new market structure. Regulatory safeguards, such as the eligibility matrix for conforming loans, were established to prevent loan quality deterioration. However, limited historical precedent and research is available on the soundness and strength of the regulation and market structure.

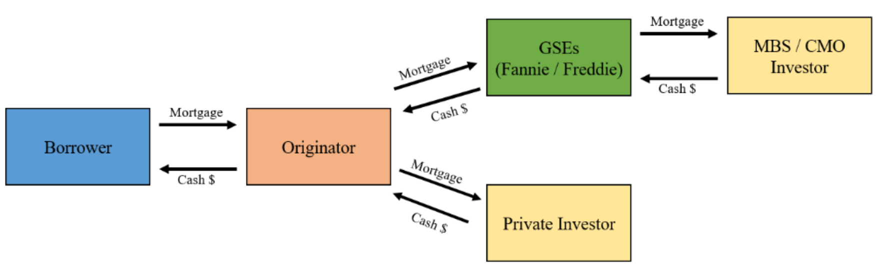
[1] See Figure XI in the Appendix.

2. BACKGROUND

2.1 Industry Structure

Mortgage originators lend money to borrowers to facilitate the purchase of a new house or to refinance an existing home. The originators then possess a mortgage note that is entitled to a monthly interest and principle payments, with the home serving as collateral. The mortgage note can either be retained on the originator's balance sheet or sold to a government-sponsored enterprise (GSE) or investor. The most prominent transaction is the sale to a GSE, such as Fannie Mae and Freddie Mac, which purchase conforming loans that meet their guideline criteria and securitize a pool of these mortgages into a mortgage-backed security (MBS). The GSEs' conforming loan standards are an eligibility matrix with different loan quality requirements based on the risk profile of the borrower. The GSEs then design a capital structure to tranch the MBS portfolio based on the priority of cash flows into collateralized mortgage obligations (CMOs). These tranches are designed to target the credit rating and risk profile of investors. Investors then purchase a tranch of the CMO based on their appetite. GSEs provide an explicit guarantee against credit risk in all CMOs. Securitization enables the transfer of interest rate and credit risk, increases liquidity, increases fee income, and enhances capital ratios (Ambrose et al. 2005). Figure I illustrates the mortgage origination supply chain process. Many studies have examined the changing structure of the mortgage origination chain with a focus on the cost and benefits analysis (Purnanandam 2011, Keys et al., 2010 and 2013, Piskorski et al., 2010, Berndt and Gupta 2009).

Figure I: Mortgage Origination Process



2.2 Industry History of Mortgage Origination

2.2.1 Pre-crisis

The mortgage origination market played a significant role in the escalation to the crisis. Innovative financing products, such as MBS and CMOs, offered higher interest rates than government securities, attractive risk rating from rating agencies, and limited exposure to default risk. The attractiveness of these products led to the increase in subprime mortgages and housing speculation (Agarwal et al., 2015 and 2017, Haughwout et al., 2016, Mayer et al., 2014).

Many transferors in the series of mortgage ownership transfers required representation and warranty clauses from the next transferee by signing a mortgage loan purchase agreement. This clause is intended to prevent misrepresentation and instill accountability, but it proved to be ineffective. The perceived assurance of contractual representation and warranties within MBS led to overinvestment in this asset class (McCoy and Wachter 2016).

Each entity along the mortgage origination supply chain earned unprecedented returns and transferred the risk along to the next entity on the chain. The exposure to mortgage risk was transferred along with the sale of the asset. In particular, most transfers from the originators were to special-purpose bankruptcy-remote entities, which granted maximal protection for the originators in the case of borrower delinquency. The risk exposure transfer led to an increase in origination volume (Ayotte and Gaon 2005). Lower quality subprime mortgages originated per year increased from historical averages of 8% to nearly 20% from 2004 to 2006 (Joint Center for Housing Studies of Harvard University).

Deterioration in loan quality was stimulated from both sides of the mortgage transaction. Originators would offer families adjustable rate mortgages (ARM) with low teaser monthly payments for the first few years that increase to a higher level, relying on the increase in housing prices to be able to re-finance the mortgage. This process enabled families with minimal income and cash to take out a loan with a high loan-to-value ratio, which would otherwise be non-conforming because of the high interest rates. The percentage of subprime mortgages originated as ARMs increased to 81 in 2006 from 51 in 1999. For the Alt-A loans, a classification of mortgages between prime and subprime, 71% of the originations were ARMs compared with the 6% over the same time period. The average combined loan-to-value ratio increased from 79% to 86% (Ashcraft and Schuermann 2008).

Many borrowers would also misrepresent themselves to earn more favorable conditions by lying about their income or manipulating their FICO scores. The Financial Crimes Enforcement Network reported 53,000 cases of mortgage fraud in 2007, up from 3,500 in 2000 (Baily et al. 2008). Many of these deceptive practices were non-issues once the borrowers were able to re-finance and unlikely to default on the mortgage. The entire mortgage structure would continue as long as housing prices continued to rise. Trends of low lending standards and higher-risk mortgage innovation products increased personal indebtedness and risk vulnerability, leading to the collapse of the housing market.

2.2.2 Financial Crisis

Declining housing prices and sharp increases in delinquency rates disrupted the entire mortgage market. Delinquency rates spiked to over 10%, reducing investor appetite for MBS and CMOs and causing a hold-up in the chain. Many earlier entities were unable to sell the risky mortgages to the next player to transfer the risk, exposing them to borrower default. In the case of delinquency, the owner of the mortgage gains possession of the home. However, the declining house prices and many underwater mortgages[2] reduced the value of CMOs and MBS. The financial service industry was flooded with subprime mortgage products of declining value. Losses to bank capital were nearly $150 billion, with many specialized mortgage banking institutions entering bankruptcy (Kregel 2008). The systemic integration of financial institutions and the rise in mortgage innovation products, such as credit default swaps and synthetic collateralized debt obligation, intensified the subprime mortgage crisis, which spread into a broader financial crisis (Barnett 2011). The catalyst of the subprime mortgage crisis was the sheer volume of subprime mortgage origination from the moral hazard originators

2.2.3 Post-crisis

The regulatory scrutiny of the mortgage industry, particularly mortgage origination, increased post-crisis. Prior to the crisis, banks and non-banks were underregulated (Kaul & Goodman 2018). Financial reform legislation, namely, the Dodd–Frank Wall Street Reform and Consumer Protection Act (Dodd–Frank), passed in 2010 increased the regulatory compliance among originators and established the Consumer Financial Protection Bureau (CFPB). Non-bank and bank originators are regulated by significantly dissimilar standards given the differences in business models and corporate structures. Unlike banks, all non-bank mortgage originators must adhere to the originator requirements of the SAFE Act and the CFPB enforcement and exams (CHLA Report). Huszar and Yu (2016) find that non-bank origination lending standards varied

[2] Home purchase loan with a lower free-market value of the home than the remaining principle

significantly based on the severity of state-based regulation before 2008. Conversely, banks are subject to strict capital and liquidity requirements by respective bank regulators and subsequent changes to the capital rules under Basel III (Mortgage Banker Association). The differences in regulatory compliance costs have created a greater differentiated cost structure for bank and non-bank origination.

Since the crisis, countless lawsuits have been filed against originators for breaching the contractual obligations in representation and warranties. Despite this agreement, loan features and performance were direct violations because of the deterioration in underwriting standards (McCoy and Wachter 2016). A 2011 study finds that two-thirds of a sample of mortgage collateral for MBSs was lower in quantity than that presented by the lender and insufficient to support the transaction (Rhee 2015). These lawsuits, as well as the associated reputational damage, became another cost for originators.

The increasing cost structure of origination has led to a significant rise in the shadow banking market share among residential mortgages. Buchak and colleagues (2017) calculate the succeeding increases. In 2007–2015, the market share of shadow banks in conforming mortgage origination nearly doubles from 30% to 50%. The increase is more prominent in the Federal Housing Administration (FHA) mortgage market that serves less creditworthy borrowers, increasing from 45% to 75% over the same period. This condition coincides with the shift in the major market players. In 2011, 50% of the mortgage origination market was held by Wells Fargo, Bank of America, and J.P. Morgan Chase, but by 2016, these banks held less than 20% (Mortgage Banker Association, 2016 Rankings). In these five years, Quicken Loans, now the third largest originator, experienced an eight-fold increase in origination volume (Creswell 2017). Shadow banks such as PennyMac Financial Services, Freedom Mortgage, Caliber Home Loans, and loanDepot have recently joined the league tables for the largest 10 originators in the United States (Mortgage Banker Association, 2016 Rankings).

2.3 Differences Among Tradition and Shadow Banks

The Federal Stability Board defines banks as depository institutions, and shadow banks are financial servicers with no consumer deposits. These definitions are consistent among regulators in 20 countries, the International Monetary Fund, the World Bank, and the Bank of International Settlements. Existing literature uses the same classification (Buchak et al., 2017). The business model, funding sources, and exposure risk distinctly differ between bank and non-bank originations.

The business models for mortgage origination differ between traditional and shadow banks. For traditional banks, mortgage origination is one of its numerous core competencies, with mortgage assets accounting for at most 0.7% of a bank's assets (Report to Congress). Traditional banks retain nearly 25% of their originated mortgages on their balance sheet, selling most of the remainder to GSEs, insurers, and other banks. Banks engage in regulatory capital arbitrage by retaining the higher-risk loans and selling the lower-risk loans to the secondary market (Ambrose et al. 2005).

By contrast, most non-banks engage in only mortgage origination and mortgage servicing. Unlike banks, non-banks hold a significant mortgage exposure and lack business diversification, leaving them vulnerable to mortgage and MBS market risks. Mortgages are particularly volatile because they are not traded on an open, observable market, and valuation is dependent on interest rates and default risks. Shadow banks have an "originate-to-distribute" model, retaining only 7.5% of originated mortgages on their balance sheet for seven days and selling government issued loans to Ginnie Mae and conforming loans to Fannie Mae and Freddie Mac. With GSEs purchasing nearly 85% of their mortgages, shadow banks are becoming increasingly reliant on the stability of GSEs (Buchak et al., 2017). Given the mixed findings on the success of GSEs in promoting their original purpose of home ownership and income equality, the continuation of these programs might change (Elenev et al. 2016, Hurst et al 2015, Bhutta 2012, Acharya et. al. 2011).

Access to funding sources differentiates the origination types. Traditional banks have stable, low-cost funding sources from consumer deposits that are insured by the Federal Deposit Insurance Corporation. Comparatively, shadow banks are reliant on external, less stable funding sources such as warehouse lending, bank loans, hedge funds, and private investors (*Attom Data Solutions*). The funding relationship between banks and non-banks creates an additional systemic risk that intensifies mortgage exposure in the industry cost (Stanton et al. 2014, 2017). Non-banks face a higher liquidity risk from maturity mismatches between its lending and borrowing as well as from the potential delinquency shocks and borrowing limits from their lenders. Additionally, non-bank servicers have lower investment credit ratings than banks, thus directly increasing their risk premium and funding (Kaul & Goodman 2018).

2.4 Recent Market Trends

2.4.1 Rising Interest Rates

The federal funds rate, the overnight inter-bank lending rate set by the Federal Reserve Bank, has experienced six rate hikes since 2016 after being at the zero-bound for nearly eight years. The 10-year treasury rate decreased from 3.858 in January 2010 to 2.989 in May 2018 (Treasury). During periods of low interest rates, many borrowers are incentivized to refinance their mortgages to receive a lower rate and increase prepayment risk. Refinance opportunities are a large revenue source for shadow banks.

Conversely, in periods of rising interest rates, non-banks experience higher funding costs. Expectancy theory explains that a surge in short-term interest rates increases all maturities across the yield curve to some degree, with larger effects on short-term rates (Cox et al. 2005). The originator can charge a higher interest rate on the mortgage, increasing the revenue value. Market competition constrains the increases in mortgage interest rates to a competitive price for customers, limiting the opportunities for excessive spread. However, non-banks face higher borrowing costs from their reliance on external funding sources, reducing origination profitability. As consumer deposits rates lag behind market interest rates, the private funding model for banks with access to cheap credit remains unchanged, enabling banks to fully benefit from the increased mortgage interest rates (Comptroller of the Currency). In a rising interest rate environment, banks' origination model becomes relatively more profitable than that of non-banks because of funding structure differences. With greater profitability, banks are more likely to re-enter the mortgage origination market, and the additional competition further diminish the mortgage rates increases when interest rates rise. This study aims to understand the effect of interest rate changes on mortgage rates between banks and shadow banks.

As only a few non-bank originators are public companies, there is a general lack of public data and minimal literature on non-bank origination. Much of the existing literature focuses on pre-recessionary trends rather than on crisis aftermath or recovery. Most studies on crisis aftermath center around the commercial mortgage market (Wong 2016, Ghent and Valkanov, 2015, An, Deng, and Gabriel, 2009) and the servicing aspect of intermediation (Kaul and Goodman 2016). The study of Buchak et al. (2017), which focuses on identifying the causes of shadow banking in the residential mortgage origination, is the only major research focusing on this specific market.

3. EXPLORING MORTGAGE ORIGINATION

3.1 Objective

The objective of this study is to better understand the strength of the mortgage origination market and its ability to withstand the pressure of the rising interest rate. Regulation intends to promote safe lending standards and consumer protectionism among financial institutions, but this study determines the changes in lending behavior between bank and non-bank originators. A scenario analysis of the loan quality metrics for traditional banks and shadow banking in the mortgage origination market is conducted on the basis of interest rates changes. The scenario analysis is similar to that of *The Report to Congress on the Effect of Capital Rules on Mortgage Servicing Assets (MSA)* on the expected effects on MSA valuation based on changes in the yield curve, swaption volatility, normal servicing cost, and constant default rate, among many other indicators (Report to Congress). A secondary regression analysis calculates the loan quality deterioration and default risk of mortgage origination over time. Altogether, a greater understanding of the responsiveness and strength of the traditional and shadow banking mortgage origination markets is provided.

3.2 Datasets

3.2.1 Fannie Mae Single-Family Loan Performance Data

Based on a subset of Fannie Mae's 30-year, fully amortizing, full documentation, single-family, fixed-rate mortgage loans, this dataset provides quarterly origination and performance data. Each quarter profiles 300,000–700,000 loans. The loan-level panel data provide information on borrower characteristics [e.g., borrower credit scores, interest rates, loan-to-value (LTV) ratios], originator name, monthly payment history [e.g., delinquency and prepayment], and loan properties. With data available from January 2000 to June 2017, the analysis focuses on pre-recessionary data from January 2010 to March 2017. Approximately 14.8 million loans are included in this analysis.

The FHA dataset, which covers FHA loans to individuals with low credit scores, provided by the U.S. Department of Housing and Urban Development would have been a more appropriate loan portfolio comparison. However, it excludes FICO scores, data essential for the analysis of this study.

3.2.2 National Mortgage Risk Index (NMRI)

The NMRI measures the safety of the mortgage lending marketing in the United States. Using the default experience of loans originating in 2007 to quantify performance after a collapse, stress tests are developed to evaluate the risk of government guaranteed loans given a financial collapse on par with the recent recession. This index developed by the American Enterprise Institute is the best measure available to quantify lending standards in the current mortgage market. It covers nearly all of government-issued mortgages and 75% of all new mortgages. In particular, it includes home purchase and refinance loans securitized and acquired by Freddie Mac and Fannie Mae or guaranteed by the FHA, Department of Veteran Affairs, or Rural Housing Services. As the data are available from September 2012 to August 2017, the analysis includes all data until March 2017 to correlate with the conforming loan data.

3.2.3 10 – Year Treasury Constant Maturity Rate

The dataset represents the historical yield curve rate for the 10-year Treasury note. The Department of Treasury derives the values daily using a quasi-cubic hermite spline function with similar inputs to the close-of-business bids for on-the-run securities (Treasury). The 10-year Treasury is often utilized as an interest rate benchmark and comparison because of its relative stability and representative qualities.

3.2.4. Effective Federal Funds Rate

The Federal Open Market Committee sets a guideline range for the federal funds rates called the overnight interbank lending rate. The effective federal funds rate is the actual market federal funds rate calculated through a volume-weighted median of overnight interbank transactions (Federal Reserve Bank of NY). The federal funds rate commonly serves as a benchmark of short-term rates.

3.3 Methodology

The Fannie Mae Single-Family Loan Performance dataset was used to determine the trends in mortgage origination between banks and non-banks since the crisis. Each loan was categorized on the basis of its type of originator, either bank or non-bank. The data were further divided according to the FICO scores of the borrower to better understand the trends among the borrower risk profiles. The summary statistics for each type of originator and borrower risk profile for all specified quarters was compiled. Further analysis on this data in comparison with the 10-year Treasury yield, federal funds rates, and NMRI predicts the effect from the interest rate increase on loan quality.

3.3.1 Categorization of Originator Type

Each of the 14.8 million loans in the acquisition data from the Fannie Mae Single-Family Loan Performance dataset was classified according to originator type. The categorization of banks and non-banks is consistent in existing literature. Gete and Reher (2017), Demyanyk and Loutskina (2016), and Huszar and Yu (2017) identify non-banks as lenders without Home Mortgage Disclosure Actcodes, as they are not under the regulatory oversight of Federal Reserve System, Federal Deposit Insurance Corporation, Office of Thrift Supervision, Office of the Comptroller of the Currency, or National Credit Union Administration. The sample also matches the manually defined list of bank and non-bank originators created by Buchak et al. (2017). Figure XXX lists the defined bank and shadow bank originators.

3.3.2 FICO Score Divide

Calculations were performed by dividing the loans into categories based on the borrower's FICO score. The FICO score ranges were as follows: below 620, 620–660, 660–700, 700–740, 740–780, and 780+. Similar to the methodology of Calem and LaCour–Little (2002), Fortowosky et al. (2011), and Ding et al. (2011), these scores represent impaired, subprime, A-, prime, and super-prime credit levels. The 40-point spread allows for more refined comparisons among the borrower risk types.

3.3.3 Summary Statistics

For each quarter, the following categories were calculated for each type of originator and borrower risk using a volume-weighted mean: total unpaid principal balance (UPB), average UPB balance, LTV, combined loan-to-value (CLTV), debt-to-income (DTI), FICO score, and note rate. These categories include all the available loan quality indicators provided in the Fannie Mae Single-Family Loan Performance dataset. Figures XII–XVII show the summary statistics for the past 28 quarters of the mortgage origination data.

3.4 Scenario Analysis

The scenario analysis calculates the expected percentage change in loan quality metrics based on interest rate movements. The selected loan quality metrics are reconcilable with those provided in the Fannie Mae dataset, including note rate, average UPB, DTI, LTV, and CLTV. The interest rate scenarios follow the parallel movement in the yield curve by negative 25 basis points (bps), negative 50 bps, negative 100 bps, positive 25 bps, positive 50 bps, and positive 100 bps. These scenarios are consistent with the hypothetical interest rate scenarios in the *Report to Congress on the Effects of Capital Rules on Mortgage Servicing Assets*. The expected changes are calculated using individual regression models for each loan quality metrics and then by computing the expected level based on interest rate bps shifts.

3.4.1 Note Rate

The expected movements in the note rate were calculated by creating a regression analysis to understand the correlation among interest and note rates. The note rate represents the agreed upon

30-year fixed mortgage rate for the borrower. The analysis uses the Fannie Mae dataset and the 10-year Treasury yields from January 2010 to March 2017.

$$rate_{i\ jzt} = \beta_0 + \beta_x T_t \ + X_i' \Gamma + \delta_{zt} + \epsilon_{i\ jzt,}$$

where $rate_{i\ jzt}$ measures the rate of the note, and T_t represents the 10-year Treasury rate to control for the interest rate effects. The regression controls for the quarter fixed effects of the lender type j and the borrower risk profile z.

3.4.2 Average Unpaid Principle Balance

The expected movements in the average UPB were calculated by creating a regression analysis to understand the correlation between the interest rates and the average UPB. This measurement calculates the size of the mortgage. The analysis uses the Fannie Mae dataset and the 10-year Treasury yields from January 2010 to March 2017.

$$Avg.UPB_{i\ jzt} = \beta_0 + \beta_x T_t \ + X_i' \Gamma + \delta_{zt} + \epsilon_{i\ jzt},$$

where $Avg.UPB_{i\ jzt}$ measures the average UPB of the note and T_t represents the 10-year Treasury rate to control for the interest rate effects. The regression controls for the quarter fixed effects of the lender type j and the borrower risk profile z.

3.4.3 Debt – to – Income

The expected movements in the DTI levels were calculated by creating a regression analysis to understand the correlation between the interest rates and the DTI. This measurement is an estimate of the borrower's ability to pay the mortgage based on income level and is usually a delinquency metric. The analysis uses the Fannie Mae dataset and the 10-year Treasury yields from January 2010 to March 2017.

$$DTI_{i\ jzt} = \beta_0 + \beta_x T_t + X_i'\Gamma + \delta_{zt} + \epsilon_{i\ jzt},$$

where $DTI_{i\ jzt}$ measures the DTI of the note, and T_t represents the 10-year Treasury rate to control for the interest rate effects. The regression controls for the quarter fixed effects of the lender type j and the borrower risk profile z.

3.4.4 Loan – to – Value Ratio

The expected movements in the LTV levels were calculated by creating a regression analysis to understand the correlation between the interest rates and the LTV. This measurement calculates the size of the borrower's equity stake and financial exposure to the home. The analysis uses the Fannie Mae dataset and the 10-year Treasury yields from January 2010 to March 2017.

$$LTV_{i\ jzt} = \beta_0 + \beta_x T_t + X_i'\Gamma + \delta_{zt} + \epsilon_{i\ jzt},$$

where $LTV_{i\ jzt}$ measures the LTV of the note, and T_t represents the 10-year Treasury rate to control for the interest rate effects. The regression controls for the quarter fixed effects of the lender type j and the borrower risk profile z.

3.4.5 Combined Loan – to – Value Ratio

The expected movements in the CLTV levels were calculated by creating a regression analysis to understand the correlation between the interest rates and the CLTV. Taking into account all loans secured by a property, this measurement calculates the size of the homeowner's equity stake and financial exposure to the home. It is usually a more comprehensive measurement than LTV. The analysis uses the Fannie Mae dataset and the 10-year Treasury yields from January 2010 to March 2017.

$$CLTV_{i\ jzt} = \beta_0 + \beta_x T_t + X_i'\Gamma + \delta_{zt} + \epsilon_{i\ jzt},$$

where $CLTV_{i\,jzt}$ measures the CLTV of the note, and T_t represents the 10-year Treasury rate to control for the interest rate effects. The regression controls for the quarter fixed effects of the lender type j and the borrower risk profile z.

3.5 Mortgage Risk Index Regression

To understand the loan quality and default risk, a final regression analysis compared the NMRI with the 10-year Treasury yield. Only the NMRI data coverage of the Fannie Mae dataset was used to ensure consistency in the analysis throughout the paper. The purpose of this regression is to determine the deterioration in loan quality in relation to the interest rate changes.

$$NMRI_{i\,jzt} = \beta_x T_t + \beta_r\, rate_{i\,jzt} + X_i'\Gamma + \delta_{zt} + \epsilon_{i\,jzt},$$

where $NMRI_{i\,jzt}$ measures the default risk of the portfolio under the same stresses of 2007, and T_t represents the 10-year Treasury rate to control for the interest rate effects. The regression controls for the quarter fixed effects of the lender type j and the borrower risk profile z.

3.6 Results

3.6.1 Scenario Analysis

The results of the effect of the parallel interest rate movements on the loan characteristics are fully detailed in Tables XVIII–XXIII in the appendix. Table II catalogs the interest rate effects on the traditional and shadow bank originated loans for borrowers with FICO scores of 620–660. The remainder of the results show the findings from the scenario analysis with supplemental charts and tables to further explain the data.

Figure II: Scenario Analysis of Loans with FICO Scores 620 - 660

	Interest Rate		Average UPB		DTI		LTV		CLTV	
	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank
100 bps	10.5%	11.5%	(7.2%)	(11.9%)	1.0%	1.2%	(4.6%)	(2.2%)	(4.5%)	(2.0%)
50 bps	5.2%	5.8%	(3.6%)	(6.0%)	0.5%	0.6%	(2.3%)	(1.1%)	(2.3%)	(1.0%)
25 bps	2.6%	2.9%	(1.8%)	(3.0%)	0.3%	0.3%	(1.1%)	(0.6%)	(1.1%)	(0.5%)
-25 bps	(2.6%)	(2.9%)	1.8%	3.0%	(0.3%)	(0.3%)	1.1%	0.6%	1.1%	0.5%
-50 bps	(5.2%)	(5.8%)	3.6%	6.0%	(0.5%)	(0.6%)	2.3%	1.1%	2.3%	1.0%
-100 bps	(10.5%)	(11.5%)	7.2%	11.9%	(1.0%)	(1.2%)	4.6%	2.2%	4.5%	2.0%

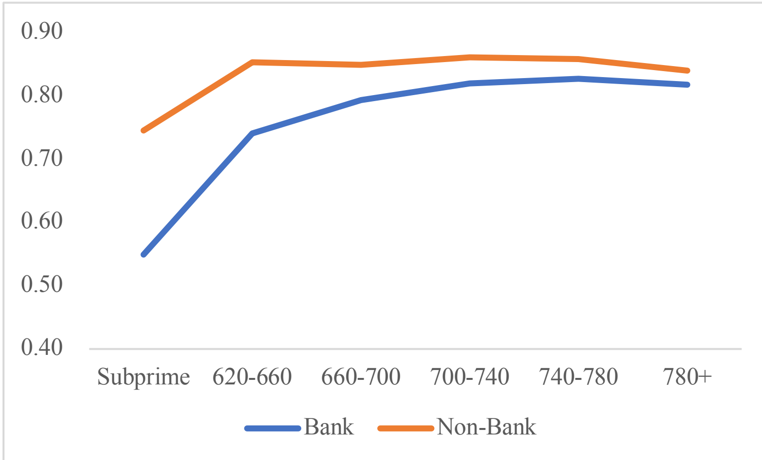
Figures XXV–XXIX in the appendix provide the summary statistics for the note rate regression, average UBP regression, DTI regression, LTV regression, and CLTV regression for banks and non-banks. The summary statistics provide information about the formulas used to extrapolate the effects of interest rates changes on loan quality. Figure III shows the summary statistics calculated for each regression using R. For all the regressions, all the values are significant at a 95% confidence interval. However, the β_0 value for non-banks and FICO scores below 620 are significant at a 90% confidence interval. Overall, the regressions are significant.

Figure III: Summary Statistics on Note Rate Regression of Non-Bank & FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.1509	0.7757	-2.773	0.00995	**
Slope	0.9952	0.1713	5.809	3.51E-06	***
RMSE	0.4281		F-statistic	20.15	
R-Squared	0.4274		P-Value	0.00012	

*Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Figure IV: Correlation among Note Rates and 10-Year Treasury by FICO Score



The scenario analysis results show that for note rates, non-banks are more sensitive to rate increases than banks. For further support, Figure IV maps the correlation between the note rates and the 10-year Treasury yields for banks and non-banks from 2010 to 2017. As the borrower's FICO score increases, the difference between the bank and non-bank correlation with the Treasury declines. At its peak for borrowers with a FICO score below 620, the gap is 36 points and narrows down to three points for top quality homeowners. The correlation for non-banks exceeds 0.75 for all profiles of borrower risk. The high correlation for non-banks is partially expected because their funding model is reliant on short-term capital from warehouse lending, bank loans, hedge funds, and private investors. By contrast, the federally insured consumer deposits used for funding mortgages for banks is less influenced by short-term rates. Assuming that the 10-year Treasury rate represents the funding cost for non-banks, this graph demonstrates the trend that mortgage origination becomes more profitable for banks than non-bank as the interest rates increase. As the bank and non-bank mortgage note rates are relatively comparable across originator types, banks earn a higher spread than subprime borrowers.

The graph also indicates that for subprime mortgages originated by banks, only half of the variation is explained by interest rate changes. The remaining variation may be attributable to other factors, such as increased risk premium due to reputational risk, legal fees, and increased regulatory burden. In general, banks are subject to more intensive capital requirements, particularly banks with over $50 billion in assets that are subject to Federal Reserve supervision.

Figure V: Rate Premium (Discount) for Non-Banks (2015 – 2017)

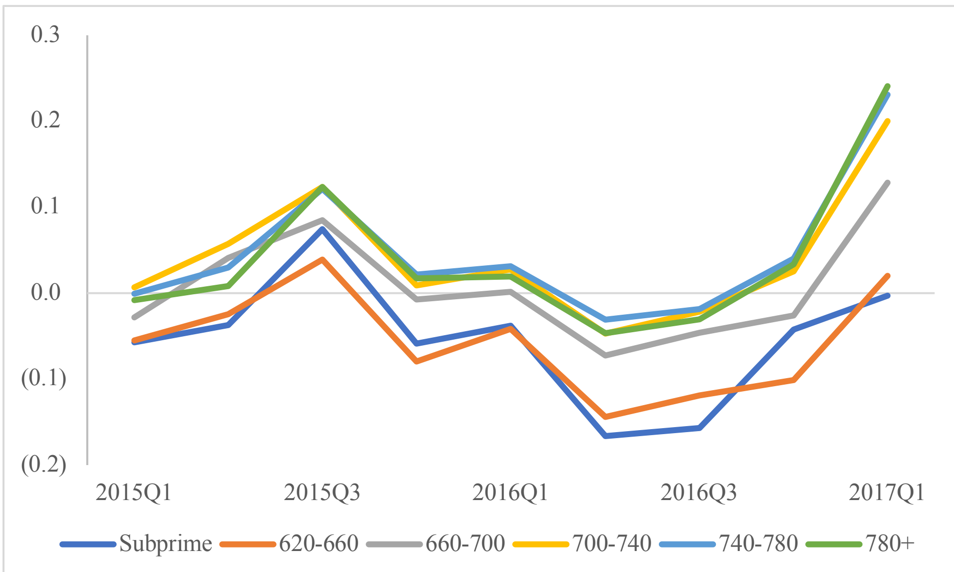
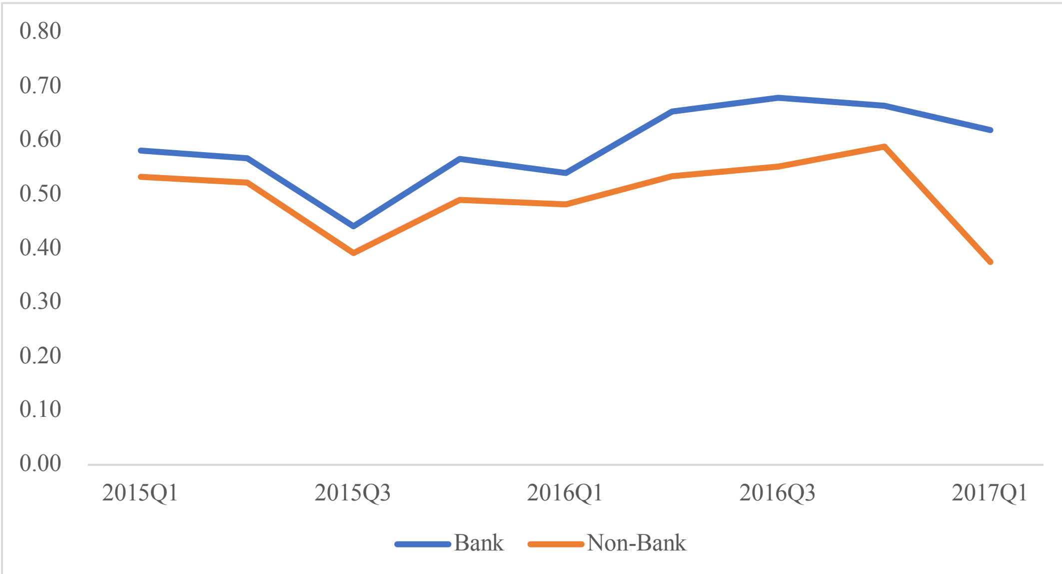


Figure V demonstrate the differences in note rates between bank and non-bank lenders. The rate premium (discount) for non-banks was calculated by subtracting the traditional bank note rate from that of the non-bank for each bucket of FICO scores. A premium indicates that non-banks charge a higher rate than banks, whereas a discount indicates that non-banks charge a lower note rate than banks. The chart shows that non-banks historically have had a competitive advantage in originating loans with lower FICO scores because they are able to charge lower rates to borrowers, particularly those with FICO scores below 660. This outcome may be attributable to the combination with higher risk premium charged by banks or the simple operational efficiency of non-banks. Banks have a competitive advantage over prime mortgages. Through the decades, traditional banks have established this dominant position. According to the Fannie Mae dataset, banks originated over 60% of the 780 plus mortgages in the first quarter of 2017.

Figure VI: Risk Spread between Prime and Subprime Borrower (2015 – 2017)



Banks charge a higher risk premium for subprime lending than non-banks. Figure VI demonstrates the risk spread between prime and subprime borrowers in 2015–2017. The risk spread was calculated by subtracting the note rate for borrowers with FICO scores below 620 from the note rate for borrowers with FICO scores above 780 for each quarter for banks and non-banks. For higher-risk borrowers, non-banks have had a lower risk premium that has narrowed over time since 2015. In 2015, there was a 5 bps differential that increased by 439% to 24 bps in 2017. Assuming that funding costs are constant across all banks and the same for all non-banks, this graph demonstrates that banks charge borrowers a higher risk premium rate than non-banks. This outcome may be attributable to the differences in business models among originators or the more intensive regulatory compliance required for banks. Further investigation is required to better understand the risk spread among banks, the distribution of origination by FICO scores for different types of banks (larger banks originating mortgages for all types of borrowers or focusing on prime mortgages), and other factors that contribute to the risk premium.

Figure VII: Average Unpaid Balance Correlation with Lagged 10-Year Treasury Yield

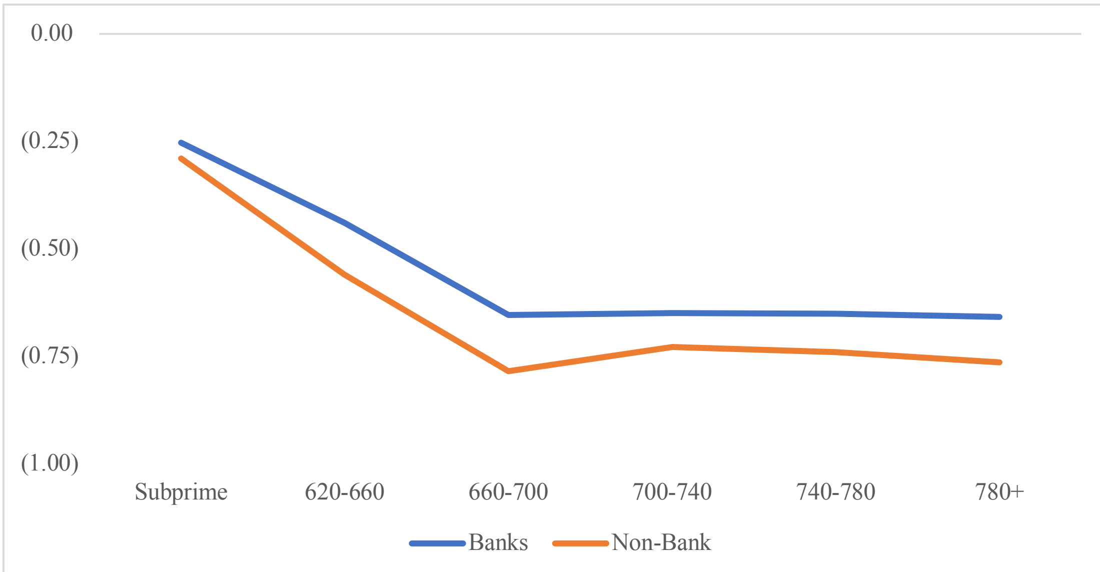


Figure VII demonstrates the correlation between the 10-year Treasury yield lagged by one quarter and the average UPB for banks and non-banks in 2015–2017. The one quarter lag allows the originator time to incorporate the changes and adjust the mortgage terms, as evidenced by the greater correlation with the mortgage data. The negative correlation indicates that as interest rates rise, the average loan size declines. Non-banks have a stronger negative correlation than banks; this result is expected because of the differences in funding costs based on originator types. The correlation declines significantly for subprime borrowers, indicating that other factors explain more of the variation. This outcome can be attributable to endogenous compounding factors that profile the type of individuals in higher-risk categories. Furthermore, the negative correlation and this graph explain the trend that as interest rates rise, the affordability of loans declines, forcing borrowers to borrower small quantities of money. In a rising interest rate environment, origination volume and UPB size are expected to decline.

Figure VIII: LTV & CTLV Correlation with Lagged 10-Year Treasury Yield (2010 – 2017)

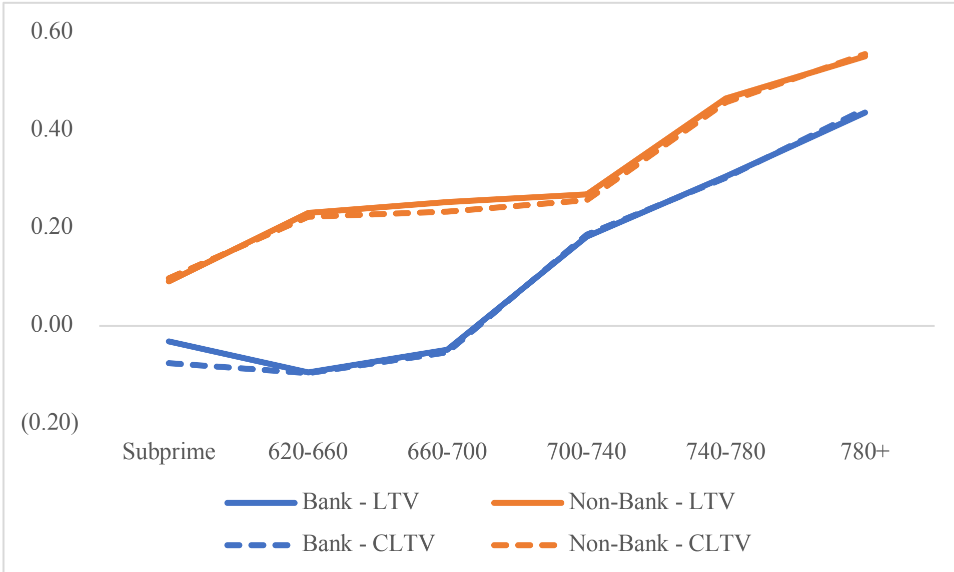


Figure VIII shows the correlation among the 10-year Treasury yield lagged by one quarter, the LTV and the CLTV for banks and non-banks. The one quarter lag enables the originator time to incorporate the changes and adjust the mortgage terms, as evidenced by the greater correlation with mortgage data. The positive correlation indicates that as the interest rates rise, less equity is required on the house. The positive trend demonstrates that the LTV and CLTV are more correlated with the interest rates as the borrower's FICO score increases. Another interpretation is that other factors, such as regulation, affect the lending standards for subprime mortgages. In particular, the Freddie Mac and Fannie Mae conforming loan requirements have an eligibility matrix with stricter requirements for more risky borrowers. This matrix demonstrates that originators prefer origin-conforming loans, emphasizing the power and influence of the conforming loan requirements as a safeguard in the mortgage market.

Figure IX: Change in Debt-to-Income Levels (2010 – 2017)

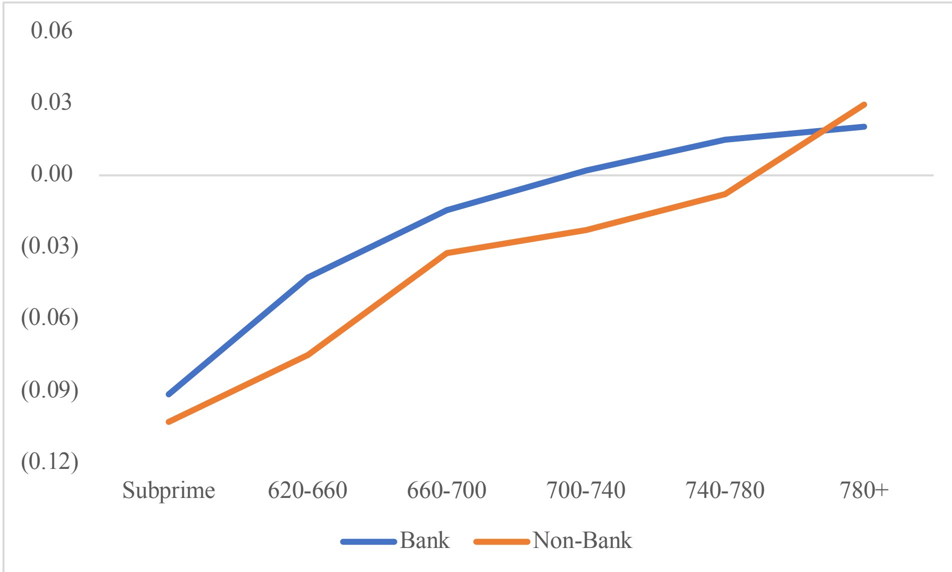
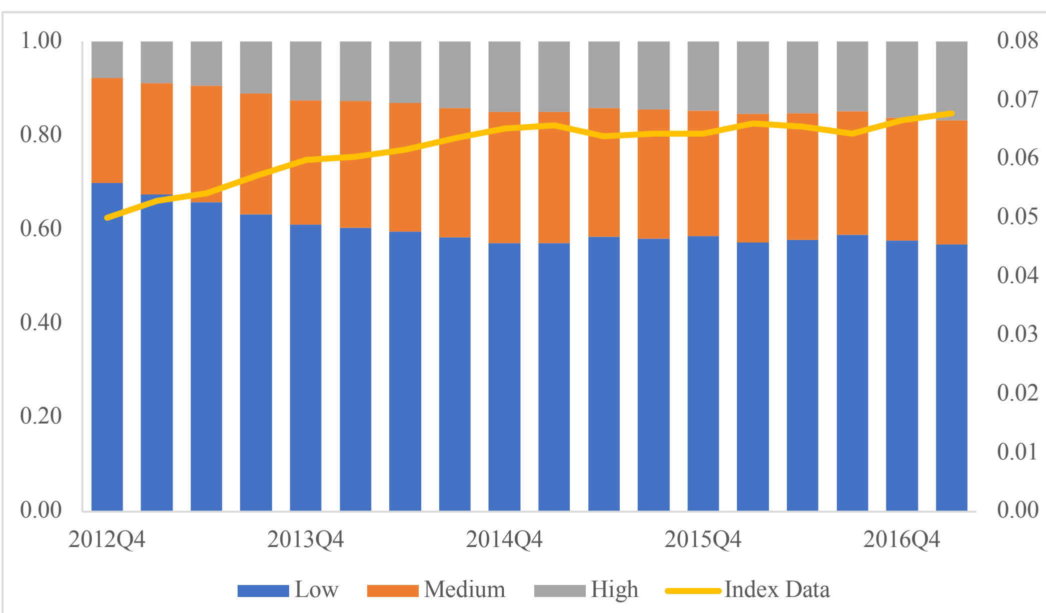


Figure IX highlights the changes in DTI levels over the past seven years. As a prominent measurement of borrower's ability to pay, DTI indicates loan quality. A decline in DTI levels shows an improvement in lending standards by requiring more income coverage, whereas an increased in DTI indicates deterioration in lending standards. In general, non-banks have demonstrated a larger relative improvement in DTI levels, but non-bank DTI levels are higher. A 10.3% and a 9.5% decrease in DTI have been found for borrowers with FICO scores below 620 for non-banks and banks, respectively. The increase of 3.0% and 2.0% in DTI for borrowers with FICO scores above 780 for non-banks and banks, respectively, may be attributable to the overly strict lending standards immediately after the crisis. Overall, DTI levels demonstrate continued improvement in lending quality across borrower risk levels.

3.6.1 National Mortgage Risk Index Regression

The results show an increase in the portion of high-risk loan origination. Overall, the portfolio default based on the NMRI index of Fannie Mae data increased by 36% since 2012. A 116% increase in the proportion of high-risk loans and an 18% increase in medium-risk loans were found from 2012. High-risk loans are defined as those having greater than a 12% default rate under the hypothetical stress scenarios modeled after the recent financial crisis, and medium-risk loans have 6%–12% stress default risk. A 0.53 correlation was found between the high-risk loans and the federal funds rate and a 0.48 correlation between the entire index and the federal funds rate. No significant correlation was observed between the NMRI and the 10-year Treasury or lagged 10-year Treasury. This dataset indicates a significant deterioration in loan quality and an increasing inability to withstand a crisis.

Figure X: Risk Profile of Fannie Mae Loans Under NMRI Stressed Conditions



4. INSIGHTS & CONCLUSIONS

4.1 Discussion

The scenario analysis indicates significant statistical evidence of the differences in loan quality between banks and non-banks based on interest rate shifts. Non-banks are more sensitive to interest rate movements than banks for the note rate, LTV, and CLTV. A higher correlation is expected because of the non-bank reliance on short-term lending for underwriting.

The analysis suggests that origination becomes increasingly more profitable for banks as interest rates rise. As funding cost structures for banks and non-bank are private information, it is only possible to extrapolate them based on revenue. The non-bank rate premium for prime borrowers has increased over 100% since the first federal funds rate hike and 280% since 2015, indicating a competitive advantage. Conversely, banks have a larger risk premium associated with subprime borrowers than non-banks. This outcome is likely attributable to the increased regulatory compliance and reputational risks relative to non-banks. As interest rates rise, the increased profitability incentivizes banks to increase their market share for prime lending, but their high-risk premium for subprime lending discourages expansion in this sector.

The scenario analysis has conflicting evidence of loan deterioration. As interest rates rise, DTI is expected to increase and LTV and CLTV to decrease, creating ambiguity in loan deterioration. Since 2010, DTI has improved to a safer level for subprime lending for banks and non-banks. More interestingly, CLTV and LTV for prime mortgages are correlated with the interest rates for prime mortgages but show no correlation with subprime mortgages. This finding may be attributable to the eligibility matrix for conforming loans set by Fannie Mae and Freddie Mac, which have stricter standards for subprime mortgages than for prime ones. The originators, especially the non-bank ones with an "originate-to-distribute" model, are particularly reliant on GSEs, value the conforming loan status, and thus adhere to these standards. The conforming loan standards are particularly important in preventing loan deterioration in a rising interest rate environment.

By contrast, the NMRI analysis indicates significant loan deterioration. With a 36% increase in the stress default rate, loan portfolio standards have clearly declined. Reconciling this with the findings from the scenario analysis, originators may be optimizing origination and maximizing returns by underwriting mortgages that exactly meet the minimum standards for conforming loans. This assumption is supported by the increase in Fintech shadow banks that offer better products by providing disruptive mortgage technology (Buchak et al. 2017). This condition ensures the perception of safe CLTV, DTI, and LTV levels, but the overall loan portfolio will only be as safe as the guidelines set by conforming loan standards.

4.2 Conclusion

The financial crisis and protectionism regulation have fundamentally changed many financial markets. Given limited historical precedence and minimal research, knowledge on the long-term effect from these significant market changes is deficient. The rise of shadow banking in mortgage origination is one small piece in the broader discussion about the effect of regulation on financial markets. The residential mortgage market is the largest consumer loan market in the United States worth over $10 trillion, representing a relevant case study on the potential risks arising from a new market structure. Without the rise of shadow banking and its associated mortgage provisions to homeowners, the cost of credit will increase, constricting the housing market and further contracting the economy. A large benefit from this change in market structure is that asset risk is diverted from systemically important financial institutions to isolated shadow banks on the surface level. While the contagion risk is contained, concerns over the creation of new risk and the longevity of these shadow banks arise.

The scenario analysis demonstrated that non-banks are more sensitive to interest rate shifts. In a rising interest rate environment, banks have relatively increased profitability and are likely to increase the prime mortgage origination market share. Banks increasing their market presence in the subprime mortgage origination market is contingent on their increased profitability exceeding their elevated risk premium. Despite the increased competition, the analysis suggests that loan quality is correlated with the interest rate as long as it still adheres to the eligibility matrix for conforming loans. These standards provide a safeguard in loan quality, preventing a race to the bottom. Loan quality will be as safe as the conforming loan requirements.

5. REFERENCES

Ashcraft, Adam B., and T. Scheurmann, 2008, Understanding the Securitization of Subprime Mortgage Credit. *Federal Reserve Bank of New York Staff Report.*

Acharya, Viral V., Matthew Richardson, Stijn Van Nieuwerburgh, and Lawrence J. White. 2011, Guaranteed to fail: Fannie Mae, Freddie Mac, and the debacle of mortgage finance. *Princeton University Press*.

Agarwal, Sumit, David Lucca, Amit Seru, and Francesco Trebbi, 2014, Inconsistent regulators: Evidence from banking, *Quarterly Journal of Economics* 129, 889-938.

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, Tomasz Piskorski, Amit Seru, 2017, Policy Intervention in Debt Renegotiation: Evidence from Home Affordable Modification Program, *Journal of Political Economy* 125, 654-712.

Ambrose, Brent W., M. Lacour-Little, and A. B. Sanders, 2005, Does Regulatory Capital Arbitrage, Reputation, or Asymmetric Information Drive Securitization? *Journal of Financial Services Research* 28:1/2/3 113–133.

Amir, E., T. S. Harris, and E. K. Venuti, 1993, A comparison of the value-relevance of US versus non-US-GAAP accounting measures using Form 20-F reconciliations. *Journal of Accounting Research* 31 (Supplement): 230–264.

An, Xudong, Yongheng Deng, and Stuart A. Gabriel, 2009, Asymmetric Information, Adverse Selection, and the Pricing of CMBS. *Journal of Financial Economics* 100:304–325.

Attom Data Solutions, 2016, The Housing News Report" Volume 10 Issue 10.

Ayotte, Kenneth M., and S. Gaon, 2005*,* Asset-Backed Securities: Costs and Benefits of "Bankruptcy Remoteness".

Bailey, Martin N., R. E. Litan, M. S. Johnson, 2008, The Origins of the Financial Crisis. *Initiative on Business and Public Policy at Brookings.*

Barnett, Harold C, 2011, And Some with a Fountain Pen: Mortgage Fraud, Securitization and the Subprime Bubble. *Columbia University Press, Forthcoming.*

Berndt, Antje, and Anurag Gupta, 2009, Moral hazard and adverse selection in the originate-to-distribute model of bank credit, *Journal of Monetary Economics* 56, 725-743.

Bhutta, Neil, 2012, GSE activity and mortgage supply in lower-income and minority neighborhoods: The effect of the affordable housing goals, *Journal of Real Estate Finance and Economics* 45, 238-261.

Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency, and National Credit Union Administration, 2016, *Report to the Congress on the Effect of Capital Rules on Mortgage Servicing Assets.*

Buchak, Greg, Gregor Matvos, Tomasz Piskorski and Amit Seru, 2017, Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks, Working paper.

Community Home Leaders Association, 2017, CHLA Report on Independent Mortgage Bankers (IMB).

Comptroller of the Currency. 2012. Interest Rate Risk Comptroller's Handbook.

Cox, John C., J. E. Ingersoll, Jr., and S. A. Ross. 2005. A Theory Of The Term Structure Of Interest Rates. *Theory of Valuation: 2nd*: 129-164.

Creswell, Julie, 2017, Quicken Loans, the New Mortgage Machine. *New York Times*

Elenev Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh, 2016, Phasing Out the GSEs, *Journal of Monetary Economics* 81, 111-132.

Federal Reserve Bank of New York. 2018. Federal Funds Data.

Ghent, Andra and Rossen Valkanov, 2015, Comparing Securitized and Balance Sheet Loans: Size Matters. *Management Science* :1–20*Articles in Advance*.

Haughwout, Andrew, Ebiere Okah, and Joseph Tracy, 2016, Second Chances: Subprime Mortgage Modification and Redefault, *Journal of Money, Credit and Banking* 48, 771-793.

Hurst, Erik, Benjamin J. Keys, Amit Seru, and Joseph Vavra, 2016, Regional redistribution through the US mortgage market, *American Economic Review* 106, 2982-3028.

Huszar, Zsuzsa, and Wei Yu. 2016. Mortgage Lending Regulatory Arbitrage: A Cross-Sectional Analysis of Nonbank Lenders. *Journal of Real Estate Research, Forthcoming*

Kaul, Karan and Laurie Goodman, 2016, Nonbank Servicer Regulation: New Capital and Liquidity Requirements Don't Offer Enough Loss Protection. *Urban Institute.*

Keys, Benjamin J., Tanmoy Mukherjee, Amit Seru, and Vikrant Vig, 2010, Did securitization lead to lax screening? Evidence from subprime loans, *Quarterly Journal of Economics* 125, 307-362.

Keys, Benjamin J., Tomasz Piskorski, Amit Seru, and Vikrant Vig, 2013, Mortgage financing in the housing boom and bust. In *Housing and Financial Crisis*, edited by Edward L.

Glaeser and Todd Sinai, 143-204, University of Chicago Press

Kregel, Jan. Changes in the U.S. Financial System and the Subprime Crisis. *The Levy Economics Institute Working Paper Collection.*

McCoy, Patricia and S. Wachter, 2016, Representatives and Warranties: Why Did They Not Stop the Crisis *Evidence and Innovation in Housing Law and Policy, Forthcoming 2017.*

Mayer, Christopher, Edward Morrison, Tomasz Piskorski, and Arpit Gupta, 2014, Mortgage modification and strategic behavior: Evidence from a legal settlement with Countrywide, *American Economic Review* 104, 2830-2857.

Mortgage Bankers Association 2016, Basel III Treatment of Mortgage Servicing Assets

Piskorski, Tomasz, Amit Seru, James Witkin, 2015, Asset Quality Misrepresentation by Financial intermediaries: Evidence from the RMBS market, *Journal of Finance* 70, 2635-2678.

Purnanandam, Amiyatosh, 2011, Originate-to-distribute model and the subprime mortgage crisis." *Review of Financial Studies* 24, 1881-1915.

Stanton, Richard, Nancy Wallace, and Jonathan Walden, 2014, The industrial organization of the U.S. residential mortgage market, *Annual Review of Financial Economics* 6*,* 259-288.

Stanton, Richard, Nancy Wallace, and Jonathan Walden, 2017, Mortgage Loan-Flow Networks and Financial Norms, working paper.

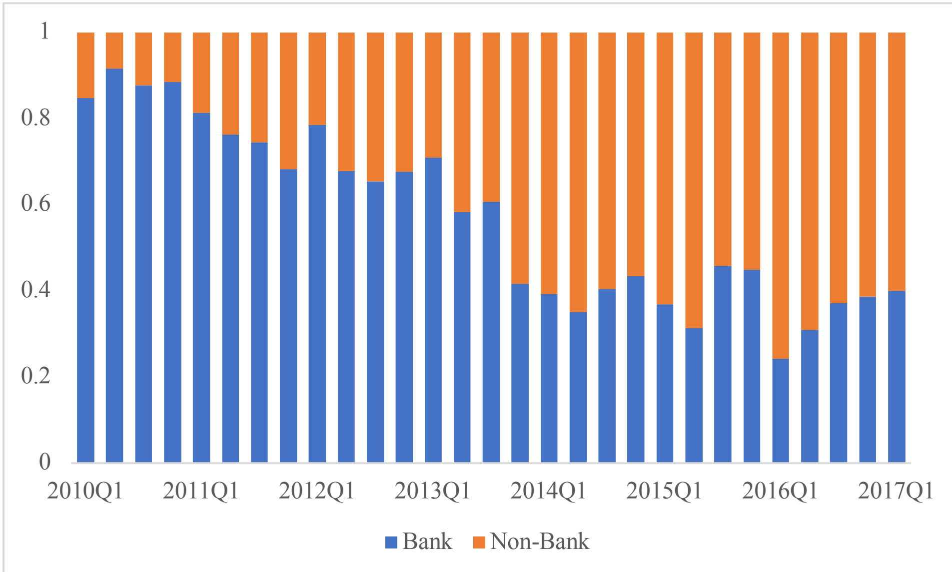
Rhee, June, 2015, Getting Residential Mortgage-Backed Securities Right: Why Governance Matters. *Stanford Journal of Law, Business & Finance 20, no. 2*: 273-322

U.S. Department of the Treasury. 2009. Treasury Yield Curve Methodology. *U.S. Department of Treasury Resource Center.*

Wong, Maisy, 2016. *CMBS and Conflicts of Interest: Evidence from Ownership Changes for Servicers*, Working Paper.

6. APPENDIX

Figure XI: Subprime Mortgage Origination by Originator Type



Non-Bank Origination Volume for Borrowers with FICO Scores 620 - 640

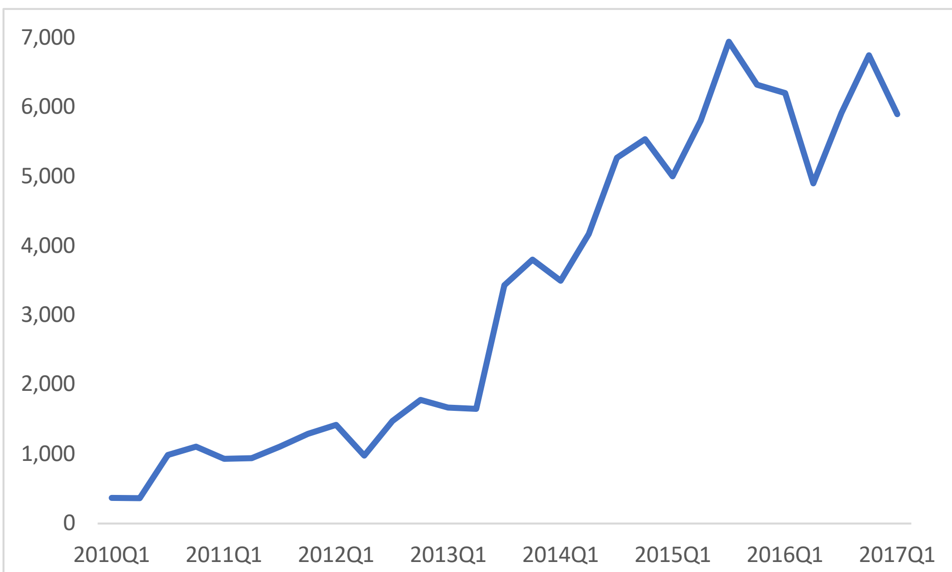


Figure XII: Summary Statistics of FICO Scores: Below 620

Bank						
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	156,614	63.4	64.2	38.5	602.5	5.39
2010Q2	155,500	64.7	64.7	35.3	604.4	5.29
2010Q3	161,258	69.7	69.9	35.1	599.7	5.22
2010Q4	169,270	69.0	69.2	34.6	588.6	4.89
2011Q1	170,964	66.7	67.3	34.1	602.8	4.58
2011Q2	153,893	67.2	67.7	34.9	603.8	5.00
2011Q3	149,970	70.9	71.5	32.4	609.4	4.86
2011Q4	160,086	73.5	74.8	36.2	607.9	4.77
2012Q1	192,065	69.8	70.4	36.4	609.9	4.50
2012Q2	167,079	66.3	66.3	36.6	616.2	4.21
2012Q3	207,556	68.7	71.2	32.3	611.2	4.12
2012Q4	202,000	68.5	70.2	33.7	606.3	3.84
2013Q1	215,589	69.8	70.6	36.2	602.0	3.89
2013Q2	209,893	68.6	70.0	36.8	608.6	4.02
2013Q3	180,647	68.0	69.0	35.4	614.0	4.10
2013Q4	205,838	71.4	71.6	35.9	611.0	4.43
2014Q1	174,625	71.7	72.6	34.8	608.0	4.53
2014Q2	177,206	72.3	73.1	37.4	619.1	4.70
2014Q3	206,661	77.1	77.6	36.9	606.8	4.65
2014Q4	199,500	74.2	74.8	38.2	611.8	4.72
2015Q1	213,044	77.3	77.6	36.7	609.6	4.52
2015Q2	180,421	68.3	68.3	36.4	617.7	4.34
2015Q3	209,804	79.4	80.8	36.8	602.9	4.33
2015Q4	217,638	79.0	79.7	36.3	607.0	4.53
2016Q1	188,419	69.7	69.7	35.1	620.0	4.45
2016Q2	197,231	71.7	71.7	35.5	620.0	4.40
2016Q3	213,275	72.8	73.2	35.6	620.0	4.25
2016Q4	205,433	70.9	71.3	36.7	620.0	4.10
2017Q1	187,150	70.0	70.5	35.0	620.0	4.36

Non-Bank						
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	156,614	63.4	64.2	38.5	602.5	5.39
2010Q2	155,500	64.7	64.7	35.3	604.4	5.29
2010Q3	161,258	69.7	69.9	35.1	599.7	5.22
2010Q4	169,270	69.0	69.2	34.6	588.6	4.89
2011Q1	170,964	66.7	67.3	34.1	602.8	4.58
2011Q2	153,893	67.2	67.7	34.9	603.8	5.00
2011Q3	149,970	70.9	71.5	32.4	609.4	4.86
2011Q4	160,086	73.5	74.8	36.2	607.9	4.77
2012Q1	192,065	69.8	70.4	36.4	609.9	4.50
2012Q2	167,079	66.3	66.3	36.6	616.2	4.21
2012Q3	207,556	68.7	71.2	32.3	611.2	4.12
2012Q4	202,000	68.5	70.2	33.7	606.3	3.84
2013Q1	215,589	69.8	70.6	36.2	602.0	3.89
2013Q2	209,893	68.6	70.0	36.8	608.6	4.02
2013Q3	180,647	68.0	69.0	35.4	614.0	4.10
2013Q4	205,838	71.4	71.6	35.9	611.0	4.43
2014Q1	174,625	71.7	72.6	34.8	608.0	4.53
2014Q2	177,206	72.3	73.1	37.4	619.1	4.70
2014Q3	206,661	77.1	77.6	36.9	606.8	4.65
2014Q4	199,500	74.2	74.8	38.2	611.8	4.72
2015Q1	213,044	77.3	77.6	36.7	609.6	4.52
2015Q2	180,421	68.3	68.3	36.4	617.7	4.34
2015Q3	209,804	79.4	80.8	36.8	602.9	4.33
2015Q4	217,638	79.0	79.7	36.3	607.0	4.53
2016Q1	188,419	69.7	69.7	35.1	620.0	4.45
2016Q2	197,231	71.7	71.7	35.5	620.0	4.40
2016Q3	213,275	72.8	73.2	35.6	620.0	4.25
2016Q4	205,433	70.9	71.3	36.7	620.0	4.10
2017Q1	187,150	70.0	70.5	35.0	620.0	4.36

Figure XIII: Summary Statistics of FICO Scores: 620 - 660

	Bank					
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	163,083	64.2	65.1	37.9	643.7	5.20
2010Q2	162,425	64.0	64.7	35.3	644.3	5.17
2010Q3	157,232	65.2	65.8	34.8	644.0	5.07
2010Q4	169,858	64.6	65.3	34.7	644.6	4.73
2011Q1	161,622	64.4	65.2	34.7	644.8	4.69
2011Q2	152,702	65.5	66.1	35.5	644.4	5.04
2011Q3	155,589	68.1	68.6	35.5	644.5	4.79
2011Q4	164,346	67.3	67.9	35.0	645.0	4.49
2012Q1	169,023	67.3	68.1	35.0	644.7	4.42
2012Q2	175,959	67.7	68.5	34.8	644.7	4.30
2012Q3	173,559	68.6	69.2	34.4	645.5	4.14
2012Q4	176,192	68.6	69.4	34.7	645.8	3.86
2013Q1	183,867	68.9	69.9	34.5	645.9	3.79
2013Q2	186,360	68.2	69.1	34.6	646.3	3.83
2013Q3	178,982	69.6	70.3	34.3	645.8	4.07
2013Q4	175,179	70.0	70.6	35.4	645.9	4.61
2014Q1	176,199	71.5	72.1	35.3	644.9	4.68
2014Q2	180,450	72.4	72.9	35.5	644.4	4.67
2014Q3	193,121	74.5	74.8	35.8	644.4	4.67
2014Q4	198,320	74.0	74.5	36.0	644.3	4.58
2015Q1	198,878	73.7	74.2	35.7	644.4	4.47
2015Q2	199,471	72.6	73.1	35.3	644.7	4.30
2015Q3	200,838	73.5	74.1	35.5	644.8	4.36
2015Q4	201,834	74.5	75.1	36.0	644.1	4.47
2016Q1	208,594	72.8	73.4	35.9	644.4	4.41
2016Q2	202,254	73.5	74.3	35.9	644.7	4.33
2016Q3	199,620	73.9	74.7	35.6	644.5	4.23
2016Q4	201,205	73.6	74.5	36.1	644.7	4.09
2017Q1	197,126	72.8	73.8	36.3	645.0	4.34

	Non-Bank					
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	146,283	64.4	64.9	39.1	643.0	5.22
2010Q2	129,743	64.7	65.3	34.7	643.2	5.06
2010Q3	154,588	66.2	66.8	35.4	643.7	5.12
2010Q4	158,412	63.6	64.4	34.9	644.1	4.77
2011Q1	156,723	65.0	66.4	35.4	644.9	4.84
2011Q2	146,386	67.8	68.2	35.8	644.0	5.15
2011Q3	149,495	66.3	66.7	35.7	644.0	4.86
2011Q4	159,646	66.5	67.2	35.6	643.7	4.48
2012Q1	159,120	65.7	66.4	35.5	643.8	4.38
2012Q2	164,837	66.2	66.9	35.1	644.3	4.27
2012Q3	172,824	67.3	67.7	34.6	644.8	4.05
2012Q4	175,142	66.4	67.1	34.9	644.8	3.87
2013Q1	190,569	66.6	67.3	35.1	644.3	3.80
2013Q2	169,098	66.7	67.3	35.1	643.6	3.86
2013Q3	179,273	68.4	69.0	35.2	644.2	4.25
2013Q4	164,357	68.7	69.2	35.7	643.2	4.62
2014Q1	169,373	68.4	68.9	35.8	643.2	4.64
2014Q2	170,969	70.1	70.5	35.8	643.5	4.69
2014Q3	177,359	70.9	71.3	36.1	643.1	4.59
2014Q4	181,518	70.8	71.2	36.0	643.4	4.59
2015Q1	191,532	70.3	70.7	36.2	643.1	4.42
2015Q2	198,364	70.7	71.1	36.1	643.3	4.28
2015Q3	195,633	70.9	71.3	36.2	642.9	4.40
2015Q4	192,137	70.3	70.7	35.8	642.8	4.39
2016Q1	195,817	69.4	69.7	36.1	642.9	4.37
2016Q2	203,987	70.6	70.9	36.1	642.9	4.19
2016Q3	205,514	69.9	70.2	36.0	642.9	4.11
2016Q4	210,115	69.2	69.5	36.0	643.0	3.99
2017Q1	199,969	69.4	69.6	36.1	642.8	4.36

Figure XIV: Summary Statistics of FICO Scores: 660 - 700

	Bank						Non-Bank					
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate	Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	192,522	66.3	67.3	37.1	683.7	5.07	182,569	65.7	66.8	37.5	683.5	5.10
2010Q2	190,551	67.0	68.0	35.1	683.9	5.07	167,554	65.9	67.0	34.1	683.1	5.00
2010Q3	192,670	67.8	68.6	34.6	684.1	4.92	183,336	68.9	69.7	35.1	683.3	4.99
2010Q4	201,870	67.5	68.5	34.3	684.4	4.58	193,433	67.1	68.2	34.3	684.2	4.58
2011Q1	195,402	67.5	68.8	34.5	684.4	4.58	182,834	67.5	69.1	34.2	684.1	4.66
2011Q2	173,782	68.1	69.0	35.4	682.9	4.95	170,674	69.3	70.2	35.2	682.8	4.98
2011Q3	183,657	70.6	71.3	35.2	683.4	4.69	172,328	70.1	70.9	35.3	683.5	4.71
2011Q4	197,123	69.8	70.7	34.6	683.6	4.35	193,524	68.6	69.6	34.8	683.9	4.33
2012Q1	195,585	69.8	70.9	34.6	683.7	4.26	188,238	68.6	69.8	34.8	683.7	4.23
2012Q2	199,103	70.6	71.5	34.7	683.8	4.16	187,242	69.8	70.7	34.7	683.9	4.16
2012Q3	202,775	71.2	72.1	34.2	684.0	3.96	201,449	71.2	72.0	34.7	684.0	3.94
2012Q4	202,788	71.1	72.1	34.0	684.1	3.71	203,895	70.8	71.6	34.6	683.7	3.73
2013Q1	208,810	70.6	71.7	34.1	683.8	3.65	214,705	70.7	71.7	34.8	683.7	3.68
2013Q2	209,634	71.1	72.1	34.5	684.1	3.74	205,877	70.2	71.1	34.6	683.8	3.71
2013Q3	203,099	73.6	74.4	34.9	683.7	4.00	202,897	73.5	74.2	35.5	682.9	4.18
2013Q4	197,616	74.0	74.7	35.6	683.1	4.56	187,216	75.0	75.5	35.9	682.3	4.59
2014Q1	198,813	74.0	74.7	35.8	682.8	4.61	195,766	74.0	74.5	36.3	682.3	4.58
2014Q2	202,814	74.7	75.4	35.7	682.7	4.56	199,425	76.2	76.7	36.1	682.2	4.64
2014Q3	210,565	76.9	77.4	35.8	682.9	4.54	206,086	75.9	76.3	36.2	681.9	4.53
2014Q4	218,094	76.3	76.9	35.9	683.1	4.46	206,611	75.4	75.9	36.4	681.8	4.52
2015Q1	217,193	75.5	76.1	35.8	683.1	4.33	217,495	74.5	75.1	36.2	682.5	4.31
2015Q2	218,592	75.1	75.8	35.4	683.1	4.14	220,723	74.0	74.5	36.3	682.1	4.18
2015Q3	218,322	76.1	76.9	35.5	683.2	4.24	217,755	75.2	75.7	36.2	682.3	4.33
2015Q4	220,386	76.5	77.3	35.8	683.2	4.32	217,293	74.5	74.9	36.1	682.5	4.32
2016Q1	225,479	75.3	76.1	35.9	682.9	4.29	224,991	73.9	74.4	36.4	682.6	4.29
2016Q2	222,321	76.5	77.4	36.0	683.9	4.16	236,600	75.2	75.6	36.1	682.9	4.09
2016Q3	217,409	76.4	77.4	35.9	683.9	4.02	231,651	73.4	73.8	36.0	682.6	3.97
2016Q4	224,163	76.0	77.0	36.0	683.8	3.88	233,817	72.7	73.0	35.9	682.9	3.86
2017Q1	214,916	75.1	76.3	36.6	683.1	4.16	219,249	73.1	73.4	36.3	682.6	4.29

Figure XV: Summary Statistics of FICO Scores: 700 – 740

	Bank							Non-Bank					
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate		Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	224,904	68.0	69.2	36.0	721.4	4.95	**2010Q1**	212,957	67.4	68.9	36.6	721.8	4.96
2010Q2	219,839	69.1	70.3	34.4	721.2	4.99	**2010Q2**	196,111	67.7	69.0	33.6	722.1	4.91
2010Q3	228,941	69.8	70.8	33.9	721.3	4.79	**2010Q3**	215,754	69.8	71.0	34.2	721.7	4.79
2010Q4	234,091	69.1	70.3	33.5	721.5	4.45	**2010Q4**	218,652	68.2	69.7	33.5	721.6	4.43
2011Q1	227,714	69.5	71.1	33.8	721.7	4.48	**2011Q1**	207,903	68.3	70.2	33.6	721.7	4.48
2011Q2	202,517	70.3	71.4	35.0	721.2	4.85	**2011Q2**	197,559	69.9	71.1	34.9	721.4	4.85
2011Q3	219,227	73.3	74.3	34.6	721.2	4.60	**2011Q3**	206,352	71.4	72.3	34.8	721.5	4.56
2011Q4	234,957	71.5	72.6	33.9	721.9	4.21	**2011Q4**	218,306	70.4	71.6	34.1	721.7	4.21
2012Q1	222,533	71.5	72.8	34.0	721.8	4.12	**2012Q1**	208,967	69.7	71.0	33.9	721.7	4.08
2012Q2	227,566	72.1	73.4	33.9	721.9	4.02	**2012Q2**	221,245	71.6	72.7	34.3	721.6	4.03
2012Q3	234,311	72.2	73.4	33.6	722.0	3.81	**2012Q3**	228,246	72.4	73.4	34.0	722.0	3.80
2012Q4	229,280	72.3	73.5	33.3	721.9	3.58	**2012Q4**	233,407	72.0	73.2	33.8	721.8	3.61
2013Q1	239,106	71.3	72.7	33.4	722.0	3.50	**2013Q1**	239,086	71.7	73.0	33.8	722.0	3.56
2013Q2	237,065	72.9	74.1	34.0	721.9	3.63	**2013Q2**	229,864	71.3	72.3	34.2	721.4	3.61
2013Q3	223,176	74.7	75.6	34.4	721.4	3.88	**2013Q3**	225,005	75.5	76.4	35.0	721.2	4.08
2013Q4	217,079	76.2	77.0	35.3	721.0	4.46	**2013Q4**	208,874	76.4	77.1	35.7	720.6	4.48
2014Q1	212,382	75.9	76.7	35.6	720.8	4.49	**2014Q1**	215,733	75.5	76.2	36.0	720.5	4.48
2014Q2	218,047	76.9	77.6	35.3	721.0	4.44	**2014Q2**	219,807	77.5	78.1	35.8	720.4	4.51
2014Q3	226,274	78.5	79.2	35.3	720.8	4.38	**2014Q3**	226,897	77.4	78.0	35.8	720.4	4.40
2014Q4	228,871	77.7	78.5	35.4	721.1	4.31	**2014Q4**	224,017	77.2	77.8	36.0	720.4	4.38
2015Q1	235,881	76.5	77.3	35.3	721.1	4.16	**2015Q1**	239,538	76.0	76.6	35.6	720.9	4.17
2015Q2	240,852	76.3	77.2	34.6	721.3	3.96	**2015Q2**	243,741	75.1	75.8	35.5	720.8	4.01
2015Q3	230,576	77.6	78.5	35.1	721.3	4.08	**2015Q3**	233,105	77.4	78.1	35.6	720.6	4.21
2015Q4	231,575	78.3	79.2	35.4	720.9	4.18	**2015Q4**	234,896	76.1	76.6	35.6	720.4	4.19
2016Q1	239,404	76.4	77.3	35.4	720.7	4.13	**2016Q1**	240,245	75.2	75.8	35.6	720.5	4.16
2016Q2	241,963	77.6	78.4	35.5	721.0	4.00	**2016Q2**	254,736	76.7	77.2	35.4	720.6	3.95
2016Q3	237,511	77.3	78.2	35.4	721.0	3.83	**2016Q3**	253,368	74.8	75.3	35.0	720.7	3.81
2016Q4	242,595	76.4	77.3	35.3	721.3	3.69	**2016Q4**	253,315	74.2	74.7	35.0	720.6	3.71
2017Q1	233,044	75.7	76.8	36.0	720.9	3.99	**2017Q1**	235,982	75.2	75.7	35.7	720.4	4.19

Figure XVI: Summary Statistics of FICO Scores: 740 - 780

	Bank							Non-Bank					
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate		Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	243,932	66.5	67.9	34.2	762.9	4.87	**2010Q1**	230,800	68.5	70.0	34.7	763.3	4.92
2010Q2	239,039	68.4	69.6	32.9	763.0	4.92	**2010Q2**	215,453	70.2	71.5	32.7	762.8	4.92
2010Q3	252,879	68.4	69.4	32.3	763.5	4.69	**2010Q3**	236,177	69.3	70.5	32.6	763.7	4.72
2010Q4	254,612	67.6	69.0	31.9	763.8	4.36	**2010Q4**	236,665	66.8	68.4	31.8	763.9	4.34
2011Q1	245,739	68.4	70.0	32.3	763.5	4.39	**2011Q1**	226,413	66.9	68.9	32.0	763.6	4.38
2011Q2	217,006	69.7	70.9	33.6	763.1	4.78	**2011Q2**	213,050	69.2	70.4	33.8	763.1	4.78
2011Q3	242,533	72.1	73.1	33.3	763.4	4.49	**2011Q3**	226,066	69.6	70.6	33.2	763.2	4.48
2011Q4	260,588	70.0	71.2	32.3	764.0	4.10	**2011Q4**	240,367	68.8	70.2	32.3	763.6	4.10
2012Q1	240,900	70.2	71.5	32.3	763.6	4.00	**2012Q1**	227,889	68.3	69.7	32.2	763.5	3.97
2012Q2	242,443	71.0	72.3	32.4	763.5	3.92	**2012Q2**	236,559	69.8	71.0	32.5	763.5	3.92
2012Q3	254,925	71.2	72.3	31.9	763.8	3.71	**2012Q3**	248,090	70.2	71.3	32.4	763.7	3.68
2012Q4	249,349	71.1	72.2	31.7	763.7	3.48	**2012Q4**	254,219	70.1	71.2	32.0	763.7	3.51
2013Q1	257,775	70.5	71.8	31.7	763.7	3.40	**2013Q1**	257,704	69.5	70.7	32.2	763.7	3.46
2013Q2	250,323	72.3	73.4	32.6	763.2	3.56	**2013Q2**	244,138	69.2	70.3	32.6	763.4	3.48
2013Q3	232,355	74.3	75.2	32.9	762.7	3.78	**2013Q3**	230,821	74.0	74.8	33.5	762.4	3.97
2013Q4	225,446	75.8	76.6	34.1	762.4	4.37	**2013Q4**	219,544	75.2	75.9	34.1	762.1	4.37
2014Q1	216,411	75.6	76.3	34.4	762.1	4.40	**2014Q1**	221,519	74.9	75.6	34.6	761.9	4.38
2014Q2	222,125	76.8	77.4	34.1	762.3	4.37	**2014Q2**	229,066	76.6	77.3	34.6	761.9	4.39
2014Q3	229,187	78.0	78.6	34.0	762.2	4.29	**2014Q3**	236,744	76.6	77.2	34.5	762.0	4.30
2014Q4	232,892	77.0	77.7	34.0	762.1	4.22	**2014Q4**	236,008	76.8	77.4	34.8	761.8	4.27
2015Q1	242,775	75.5	76.2	34.0	762.3	4.04	**2015Q1**	253,568	74.8	75.4	34.3	762.1	4.04
2015Q2	250,120	75.5	76.4	33.4	762.4	3.86	**2015Q2**	254,656	73.7	74.4	34.2	762.2	3.89
2015Q3	238,390	76.8	77.6	33.8	762.1	3.97	**2015Q3**	237,915	76.6	77.3	34.2	761.6	4.09
2015Q4	236,019	77.6	78.3	34.0	761.9	4.06	**2015Q4**	238,584	75.5	76.0	34.3	761.7	4.08
2016Q1	243,596	75.4	76.0	34.0	762.0	4.00	**2016Q1**	245,298	74.7	75.2	34.5	761.8	4.04
2016Q2	250,570	76.2	76.8	34.1	762.1	3.85	**2016Q2**	262,382	75.9	76.4	34.1	762.0	3.82
2016Q3	246,590	75.7	76.3	33.8	762.3	3.68	**2016Q3**	264,591	73.4	73.9	33.7	762.3	3.66
2016Q4	253,380	74.5	75.1	33.6	762.2	3.54	**2016Q4**	261,877	72.7	73.2	33.5	762.2	3.58
2017Q1	241,760	74.1	74.8	34.7	761.8	3.85	**2017Q1**	239,512	74.5	74.9	34.4	761.4	4.08

Figure XVII: Summary Statistics of FICO Scores: 780+

	Bank					
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	234,681	62.3	63.5	31.5	796.6	4.82
2010Q2	226,759	63.9	64.9	30.6	796.9	4.87
2010Q3	242,687	63.3	64.1	29.8	797.7	4.59
2010Q4	243,855	63.0	64.0	29.3	798.1	4.28
2011Q1	233,293	63.9	65.1	29.9	797.6	4.32
2011Q2	207,392	66.2	67.0	31.4	797.6	4.73
2011Q3	234,003	67.4	68.2	30.9	797.7	4.38
2011Q4	257,182	64.9	65.9	29.7	798.4	4.00
2012Q1	238,422	64.9	66.0	29.6	798.5	3.91
2012Q2	238,942	65.7	66.6	29.7	798.7	3.83
2012Q3	251,935	66.3	67.1	29.3	798.3	3.62
2012Q4	243,839	66.1	66.9	29.0	798.3	3.40
2013Q1	252,648	65.6	66.5	29.0	798.1	3.32
2013Q2	244,041	67.2	68.0	30.1	798.1	3.49
2013Q3	227,176	69.0	69.7	30.4	798.0	3.67
2013Q4	219,452	71.4	72.0	31.8	797.2	4.30
2014Q1	210,271	70.8	71.4	32.0	797.4	4.30
2014Q2	219,109	72.3	72.9	31.8	797.6	4.28
2014Q3	224,341	73.2	73.7	31.8	797.7	4.19
2014Q4	228,093	72.4	72.9	31.7	797.8	4.13
2015Q1	238,410	70.6	71.1	31.5	797.8	3.93
2015Q2	243,966	70.4	71.0	30.9	798.1	3.77
2015Q3	234,519	71.6	72.1	31.4	798.0	3.88
2015Q4	231,899	72.5	73.0	31.6	797.7	3.96
2016Q1	240,172	70.3	70.8	31.6	797.9	3.91
2016Q2	248,052	70.9	71.3	31.7	797.9	3.75
2016Q3	245,923	69.9	70.3	31.2	798.3	3.57
2016Q4	252,353	68.3	68.7	30.9	798.4	3.44
2017Q1	240,767	68.4	69.0	32.2	797.9	3.74

	Non-Bank					
	Average UBP	LTV	CLTV	DTI	FICO	Note Rate
2010Q1	226,207	64.5	65.9	31.2	797.4	4.86
2010Q2	214,017	66.4	67.6	30.0	797.7	4.87
2010Q3	229,740	64.4	65.5	29.7	798.3	4.63
2010Q4	226,312	61.6	63.1	28.9	798.8	4.27
2011Q1	214,654	61.5	63.2	29.2	798.2	4.27
2011Q2	205,289	65.1	66.1	31.2	798.0	4.71
2011Q3	220,137	64.9	65.8	30.7	798.1	4.36
2011Q4	232,623	63.7	64.7	29.5	798.5	3.99
2012Q1	226,657	62.7	63.7	29.4	798.5	3.86
2012Q2	231,618	64.4	65.2	30.1	798.8	3.82
2012Q3	244,475	64.7	65.5	29.7	798.3	3.58
2012Q4	251,114	64.5	65.4	29.4	798.3	3.41
2013Q1	251,707	63.9	64.8	29.6	798.4	3.37
2013Q2	237,740	63.3	64.2	29.6	798.7	3.35
2013Q3	230,728	69.0	69.6	31.0	797.6	3.86
2013Q4	216,541	70.3	70.9	31.6	797.3	4.26
2014Q1	219,916	70.3	70.8	32.3	797.0	4.27
2014Q2	226,676	72.1	72.6	32.1	797.5	4.29
2014Q3	233,811	72.4	72.9	32.1	797.5	4.19
2014Q4	235,096	72.4	72.8	32.2	797.4	4.18
2015Q1	255,012	70.2	70.6	31.7	797.4	3.93
2015Q2	252,876	68.6	69.1	31.7	798.1	3.78
2015Q3	234,469	72.2	72.7	31.9	797.7	4.01
2015Q4	237,838	71.1	71.5	32.0	797.5	3.98
2016Q1	245,137	70.1	70.5	32.0	797.5	3.93
2016Q2	260,805	70.7	71.0	31.7	797.9	3.70
2016Q3	263,463	67.6	68.0	31.0	798.1	3.54
2016Q4	261,402	66.8	67.2	30.9	798.2	3.47
2017Q1	235,281	70.1	70.5	32.2	797.4	3.98

Figure XVIII: Summary Statistics of Loan Quality in Stress Scenarios – FICO: Below 620

	Note Rate		Average UPB		DTI		LTV		CLTV	
	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank
100 bps	10.7%	12.2%	(11.3%)	(14.7%)	0.9%	(0.2%)	(3.7%)	(1.6%)	(4.0%)	(0.8%)
50 bps	5.4%	6.1%	(5.7%)	(7.3%)	0.4%	(0.1%)	(1.8%)	(0.8%)	(2.0%)	(0.4%)
25 bps	2.7%	3.0%	(2.8%)	(3.7%)	0.2%	(0.1%)	(0.9%)	(0.4%)	(1.0%)	(0.2%)
-25 bps	(2.7%)	(3.0%)	2.8%	3.7%	(0.2%)	0.1%	0.9%	0.4%	1.0%	0.2%
-50 bps	(5.4%)	(6.1%)	5.7%	7.3%	(0.4%)	0.1%	1.8%	0.8%	2.0%	0.4%
-100 bps	(10.7%)	(12.2%)	11.3%	14.7%	(0.9%)	0.2%	3.7%	1.6%	4.0%	0.8%

Figure XIX: Summary Statistics of Loan Quality in Stress Scenarios – FICO: 620 – 660

	Interest Rate		Average UPB		DTI		LTV		CLTV	
	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank
100 bps	10.5%	11.5%	(7.2%)	(11.9%)	1.0%	1.2%	(4.6%)	(2.2%)	(4.5%)	(2.0%)
50 bps	5.2%	5.8%	(3.6%)	(6.0%)	0.5%	0.6%	(2.3%)	(1.1%)	(2.3%)	(1.0%)
25 bps	2.6%	2.9%	(1.8%)	(3.0%)	0.3%	0.3%	(1.1%)	(0.6%)	(1.1%)	(0.5%)
-25 bps	(2.6%)	(2.9%)	1.8%	3.0%	(0.3%)	(0.3%)	1.1%	0.6%	1.1%	0.5%
-50 bps	(5.2%)	(5.8%)	3.6%	6.0%	(0.5%)	(0.6%)	2.3%	1.1%	2.3%	1.0%
-100 bps	(10.5%)	(11.5%)	7.2%	11.9%	(1.0%)	(1.2%)	4.6%	2.2%	4.5%	2.0%

Figure XX: Summary Statistics of Loan Quality in Stress Scenarios – FICO: 620 – 660

	Interest Rate		Average UPB		DTI		LTV		CLTV	
	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank
100 bps	11.3%	11.8%	(5.2%)	(9.1%)	1.0%	0.1%	(4.1%)	(3.2%)	(4.0%)	(2.9%)
50 bps	5.6%	5.9%	(2.6%)	(4.6%)	0.5%	0.1%	(2.0%)	(1.6%)	(2.0%)	(1.5%)
25 bps	2.8%	2.9%	(1.3%)	(2.3%)	0.2%	0.0%	(1.0%)	(0.8%)	(1.0%)	(0.7%)
-25 bps	(2.8%)	(2.9%)	1.3%	2.3%	(0.2%)	(0.0%)	1.0%	0.8%	1.0%	0.7%
-50 bps	(5.6%)	(5.9%)	2.6%	4.6%	(0.5%)	(0.1%)	2.0%	1.6%	2.0%	1.5%
-100 bps	(11.3%)	(11.8%)	5.2%	9.1%	(1.0%)	(0.1%)	4.1%	3.2%	4.0%	2.9%

Figure XXI: Summary Statistics of Loan Quality in Stress Scenarios – FICO: 660 – 700

	Interest Rate		Average UPB		DTI		LTV		CLTV	
	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank
100 bps	12.1%	12.1%	(3.8%)	(7.7%)	0.8%	0.4%	(3.4%)	(3.2%)	(3.3%)	(2.8%)
50 bps	6.1%	6.1%	(1.9%)	(3.8%)	0.4%	0.2%	(1.7%)	(1.6%)	(1.6%)	(1.4%)
25 bps	3.0%	3.0%	(1.0%)	(1.9%)	0.2%	0.1%	(0.9%)	(0.8%)	(0.8%)	(0.7%)
-25 bps	(3.0%)	(3.0%)	1.0%	1.9%	(0.2%)	(0.1%)	0.9%	0.8%	0.8%	0.7%
-50 bps	(6.1%)	(6.1%)	1.9%	3.8%	(0.4%)	(0.2%)	1.7%	1.6%	1.6%	1.4%
-100 bps	(12.1%)	(12.1%)	3.8%	7.7%	(0.8%)	(0.4%)	3.4%	3.2%	3.3%	2.8%

Figure XXII: Summary Statistics of Loan Quality in Stress Scenarios – FICO: 700 – 740

	Interest Rate		Average UPB		DTI		LTV		CLTV	
	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank
100 bps	13.0%	13.3%	(3.1%)	(6.9%)	0.8%	0.6%	(3.3%)	(1.9%)	(3.0%)	(1.4%)
50 bps	6.5%	6.7%	(1.6%)	(3.5%)	0.4%	0.3%	(1.7%)	(0.9%)	(1.5%)	(0.7%)
25 bps	3.3%	3.3%	(0.8%)	(1.7%)	0.2%	0.1%	(0.8%)	(0.5%)	(0.8%)	(0.4%)
-25 bps	(3.3%)	(3.3%)	0.8%	1.7%	(0.2%)	(0.1%)	0.8%	0.5%	0.8%	0.4%
-50 bps	(6.5%)	(6.7%)	1.6%	3.5%	(0.4%)	(0.3%)	1.7%	0.9%	1.5%	0.7%
-100 bps	(13.0%)	(13.3%)	3.1%	6.9%	(0.8%)	(0.6%)	3.3%	1.9%	3.0%	1.4%

Figure XXIII: Summary Statistics of Loan Quality in Stress Scenarios – FICO: 780+

	Interest Rate		Average UPB		DTI		LTV		CLTV	
	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank	Bank	Non-Bank
100 bps	13.8%	14.1%	(5.3%)	(7.9%)	1.2%	0.0%	(2.8%)	(1.2%)	(2.5%)	(0.7%)
50 bps	6.9%	7.0%	(2.6%)	(3.9%)	0.6%	0.0%	(1.4%)	(0.6%)	(1.3%)	(0.3%)
25 bps	3.4%	3.5%	(1.3%)	(2.0%)	0.3%	0.0%	(0.7%)	(0.3%)	(0.6%)	(0.2%)
-25 bps	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
-50 bps	(3.4%)	(3.5%)	1.3%	2.0%	(0.3%)	(0.0%)	0.7%	0.3%	0.6%	0.2%
-100 bps	(6.9%)	(7.0%)	2.6%	3.9%	(0.6%)	(0.0%)	1.4%	0.6%	1.3%	0.3%

Figure XXV: Summary Statistics on Note Rate Regression
Banks FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.7994	0.9248	-1.946	0.06216	.
Slope	0.9158	0.204	4.489	0.00012	***
RMSE	0.4281		F-statistic	20.15	
R-Squared	0.4274		P-Value	0.00012	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.1509	0.7757	-2.773	0.00995	**
Slope	0.9952	0.1713	5.809	3.51E-06	***
RMSE	0.4281		F-statistic	20.15	
R-Squared	0.4274		P-Value	0.00012	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.2017	0.9398	-2.343	0.0268	*
Slope	1.0139	0.2092	4.846	4.61E-05	***
RMSE	20.15		F-statistic	23.48	
R-Squared	0.00012		P-Value	4.61E-05	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.3814	0.8239	-2.89	0.00751	**
Slope	1.0556	0.1837	5.748	4.13E-06	***
RMSE	0.3794		F-statistic	33.03	
R-Squared	0.5503		P-Value	4.13E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXV: Summary Statistics on Note Rate Regression
Banks FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.0648	0.8544	-2.417	0.0227	*
Slope	1.0133	0.1959	5.172	1.92E-05	***
RMSE	0.401		F-statistic	26.75	
R-Squared	0.4976		P-Value	1.92E-05	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.2314	0.8062	-2.768	0.0101	*
Slope	1.0475	0.1841	5.688	4.83E-06	***
RMSE	0.3816		F-statistic	32.36	
R-Squared	0.5451		P-Value	4.83E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.8104	0.7813	-2.317	0.0283	*
Slope	0.9862	0.185	5.332	1.25E-05	***
RMSE	0.3949		F-statistic	28.43	
R-Squared	0.5129		P-Value	1.25E-05	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.1659	0.7782	-2.783	0.00971	**
Slope	1.065	0.1833	5.81	3.5E-06	***
RMSE	0.3772		F-statistic	33.75	
R-Squared	0.5556		P-Value	3.5E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXV: Summary Statistics on Note Rate Regression
Banks FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.6446	0.7313	-2.249	0.0329	*
Slope	0.9707	0.1774	5.472	8.6E-06	***
RMSE	0.3896		F-statistic	29.94	
R-Squared	0.5258		P-Value	8.6E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.8589	0.7087	-2.623	0.0142	*
Slope	1.0172	0.171	5.949	2.42E-06	***
RMSE	0.3722		F-statistic	35.39	
R-Squared	0.5672		P-Value	2.42E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.5278	0.6942	-2.201	0.0365	*
Slope	0.9631	0.1721	5.597	6.16E-06	***
RMSE	0.3849		F-statistic	31.33	
R-Squared	0.5371		P-Value	6.16E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.6624	0.6695	-2.483	0.0195	*
Slope	0.9936	0.1655	6.005	2.09E-06	***
RMSE	0.3702		F-statistic	36.06	
R-Squared	0.5718		P-Value	2.09E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVI: Summary Statistics on Average Unpaid Balance Regression

Banks FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	4.891e+00	7.826e-01	6.249	1.1e-06	***
Slope	-1.364e-05	4.154e-06	-3.284	0.00283	**
RMSE	0.4782		F-statistic	10.79	
R-Squared	0.2854		P-Value	0.002832	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.7994	0.9248	-1.946	0.06216	.
Slope	0.9158	0.2040	4.489	0.00012	***
RMSE	0.4281		F-statistic	20.15	
R-Squared	0.4274		P-Value	0.00012	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	5.179e+00	1.017e	5.092	2.38e-05	***
Slope	-1.566e-05	5.581e-06	-2.806	0.00919	**
RMSE	0.4978		F-statistic	7.873	
R-Squared	0.2258		P-Value	0.009193	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.2017	0.9398	-2.343	0.0268	*
Slope	1.0139	0.2092	4.846	4.61e-05	***
RMSE	0.4138		F-statistic	23.48	
R-Squared	0.4651		P-Value	4.612e-05	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVI: Summary Statistics on Average Unpaid Balance Regression
Banks FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	6.447e	1.509e	4.273	0.000214	***
Slope	-2.001e-05	7.333e-06	-2.729	0.011034	*
RMSE	0.5009		F-statistic	7.449	
R-Squared	0.2162		P-Value	0.01103	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	5.483e	9.642e-01	5.686	4.85e-06	***
Slope	-1.555e-05	4.747e-06	-3.277	0.00289	**
RMSE	0.4786		F-statistic	10.74	
R-Squared	0.2845		P-Value	0.002886	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	8.770e	2.263e	3.876	0.000614	***
Slope	-2.809e-05	9.873e-06	-2.845	0.008364	**
RMSE	0.4962		F-statistic	8.096	
R-Squared	0.2307		P-Value	0.008364	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.8104	0.7813	-2.317	0.0283	*
Slope	0.9862	0.1850	5.332	1.25e-05	***
RMSE	0.3949		F-statistic	28.43	
R-Squared	0.5129		P-Value	1.25e-05	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVI: Summary Statistics on Average Unpaid Balance Regression
Banks FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	6.074e	2.096e	2.898	0.00737	**
Slope	-1.545e-05	8.657e-06	-1.785	0.08549	
RMSE	0.5351		F-statistic	3.187	
R-Squared	0.1056		P-Value	0.08549	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.6446	0.7313	-2.249	0.0329	*
Slope	0.9707	0.1774	5.472	8.6e-06	***
RMSE	0.3896		F-statistic	29.94	
R-Squared	0.5258		P-Value	8.603e-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	7.597e	1.779e	4.271	0.000215	***
Slope	-2.226e-05	7.516e-06	-2.961	0.006317	**
RMSE	0.4915		F-statistic	8.769	
R-Squared	0.2452		P-Value	0.006317	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.5278	0.6942	-2.201	0.0365	*
Slope	0.9631	0.1721	5.597	6.16e-06	***
RMSE	0.3849		F-statistic	31.33	
R-Squared	0.5371		P-Value	6.156e-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVII: Summary Statistics on Debt – To – Income Regression

Banks FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	0.68795	2.61795	0.263	0.795	.
Slope	0.04617	0.07325	0.630	0.534	***
RMSE	0.5616		F-statistic	0.3974	
R-Squared	0.0145		P-Value	0.5338	

*Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Non-Bank FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	2.613945	2.033631	1.285	0.210	**
Slope	-0.007814	0.057279	-0.136	0.893	***
RMSE	0.5656		F-statistic	0.01861	
R-Squared	0.0006888		P-Value	0.8925	

*Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Banks FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-4.9406	4.8808	-1.012	0.320	*
Slope	0.2057	0.1379	1.491	0.147	***
RMSE	0.5438		F-statistic	2.224	
R-Squared	0.07611		P-Value	0.1475	

*Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Non-Bank FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-5.1240	4.4931	-1.140	0.264	**
Slope	0.2088	0.1257	1.661	0.108	***
RMSE	0.5389		F-statistic	2.759	
R-Squared	0.0927		P-Value	0.1083	

*Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Figure XXVII: Summary Statistics on Debt – To – Income Regression
Banks FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-3.5988	4.6649	-0.771	0.447	*
Slope	0.1682	0.1321	1.273	0.214	***
RMSE	0.5495		F-statistic	1.62	
R-Squared	0.0566		P-Value	0.214	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	1.54327	4.44947	0.347	0.731	*
Slope	0.02234	0.12519	0.178	0.860	***
RMSE	0.5654		F-statistic	0.03183	
R-Squared	0.001178		P-Value	0.8597	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.8615	4.4223	-0.421	0.677	*
Slope	0.1210	0.1274	0.950	0.351	***
RMSE	0.5565		F-statistic	0.9018	
R-Squared	0.03232		P-Value	0.3507	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	0.56946	4.15398	0.137	0.892	**
Slope	0.05062	0.11892	0.426	0.674	***
RMSE	0.5639		F-statistic	0.1811	
R-Squared	0.006664		P-Value	0.6738	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVII: Summary Statistics on Debt – To – Income Regression
Banks FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.1320	3.8427	-0.295	0.771	*
Slope	0.1043	0.1155	0.903	0.374	***
RMSE	0.5574		F-statistic	0.8155	
R-Squared	0.02932		P-Value	0.3745	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	0.31538	3.57592	0.088	0.930	*
Slope	0.06041	0.10682	0.566	0.576	***
RMSE	0.5624		F-statistic	0.3199	
R-Squared	0.01171		P-Value	0.5764	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.0621	3.1980	-0.332	0.742	*
Slope	0.1105	0.1039	1.063	0.297	***
RMSE	0.5543		F-statistic	1.131	
R-Squared	0.0402		P-Value	0.297	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	2.250979	2.953702	0.762	0.453	*
Slope	0.002786	0.095701	0.029	0.977	***
RMSE	0.5657		F-statistic	0.0008472	
R-Squared	3.138e-05		P-Value	0.977	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVIII: Summary Statistics on LTV Regression
Banks FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	6.00464	1.79509	3.345	0.00243	.
Slope	-0.05187	0.02535	-2.046	0.05058	***
RMSE	0.5264		F-statistic	4.187	
R-Squared	0.1343		P-Value	0.05058	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	3.74674	1.78556	2.098	0.0454	**
Slope	-0.02074	0.02623	-0.791	0.4359	***
RMSE	0.5593		F-statistic	0.6256	
R-Squared	0.02264		P-Value	0.4359	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	7.73965	1.81773	4.258	0.000223	*
Slope	-0.07735	0.02599	-2.976	0.006094	***
RMSE	0.4909		F-statistic	8.857	
R-Squared	0.247		P-Value	0.006094	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	8.75477	3.01477	2.904	0.00726	**
Slope	-0.09441	0.04432	-2.130	0.04244	***
RMSE	0.5235		F-statistic	4.537	
R-Squared	0.1439		P-Value	0.04244	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVIII: Summary Statistics on LTV Regression
Banks FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	7.82026	1.96878	3.972	0.000476	*
Slope	-0.07568	0.02714	-2.788	0.009590	***
RMSE	0.4985		F-statistic	7.774	
R-Squared	0.2236		P-Value	0.00959	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	7.52864	2.22763	3.380	0.00222	*
Slope	-0.07235	0.03101	-2.333	0.02736	***
RMSE	0.5161		F-statistic	5.442	
R-Squared	0.1677		P-Value	0.02736	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	7.74811	2.18624	3.544	0.00146	*
Slope	-0.07316	0.02953	-2.477	0.01978	***
RMSE	0.5107		F-statistic	6.138	
R-Squared	0.1852		P-Value	0.01978	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	7.27135	2.18410	3.329	0.00253	**
Slope	-0.06743	0.02982	-2.261	0.03199	***
RMSE	0.5188		F-statistic	5.114	
R-Squared	0.1593		P-Value	0.03199	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXVIII: Summary Statistics on LTV Regression
Banks FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	6.97571	2.10573	3.313	0.00263	*
Slope	-0.06357	0.02883	-2.205	0.03613	***
RMSE	0.5208		F-statistic	4.863	
R-Squared	0.1526		P-Value	0.03613	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Non-Bank FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	5.10872	2.29062	2.230	0.0342	*
Slope	-0.03842	0.03171	-1.211	0.2363	***
RMSE	0.551		F-statistic	1.467	
R-Squared	0.05154		P-Value	0.2363	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Banks FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	6.06788	2.09308	2.899	0.00735	*
Slope	-0.05485	0.03074	-1.785	0.08558	***
RMSE	0.5351		F-statistic	3.185	
R-Squared	0.1055		P-Value	0.08558	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Non-Bank FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	3.68586	2.01866	1.826	0.0789	*
Slope	-0.02007	0.02999	-0.669	0.5091	***
RMSE	0.5611		F-statistic	0.4477	
R-Squared	0.01631		P-Value	0.5091	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Figure XXIX: Summary Statistics on CLTV Regression
Banks FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.7994	0.9248	-1.946	0.06216	.
Slope	0.9158	0.204	4.489	0.00012	***
RMSE	0.4281		F-statistic	20.15	
R-Squared	0.4274		P-Value	0.00012	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: Below 620

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.1509	0.7757	-2.773	0.00995	**
Slope	0.9952	0.1713	5.809	3.51E-06	***
RMSE	0.5644		F-statistic	0.1264	
R-Squared	0.00466		P-Value	0.7249	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.2017	0.9398	-2.343	0.0268	*
Slope	1.0139	0.2092	4.846	4.61E-05	***
RMSE	0.4138		F-statistic	23.48	
R-Squared	0.4651		P-Value	4.61E-05	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 620 – 660

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.3814	0.8239	-2.89	0.00751	**
Slope	1.0556	0.1837	5.748	4.13E-06	***
RMSE	0.5253		F-statistic	4.317	
R-Squared	0.1379		P-Value	0.04736	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXIX: Summary Statistics on CLTV Regression
Banks FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.0648	0.8544	-2.417	0.0227	*
Slope	1.0133	0.1959	5.172	1.92E-05	***
RMSE	0.4966		F-statistic	8.048	
R-Squared	0.2296		P-Value	0.008537	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 660 – 700

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.2314	0.8062	-2.768	0.0101	*
Slope	1.0475	0.1841	5.688	4.83E-06	***
RMSE	0.5165		F-statistic	5.4	
R-Squared	0.1667		P-Value	0.0279	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.8104	0.7813	-2.317	0.0283	*
Slope	0.9862	0.185	5.332	1.25E-05	***
RMSE	0.3949		F-statistic	28.43	
R-Squared	0.5129		P-Value	1.25E-05	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 700 – 740

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-2.1659	0.7782	-2.783	0.00971	**
Slope	1.065	0.1833	5.81	3.5E-06	***
RMSE	0.5215		F-statistic	4.78	
R-Squared	0.1504		P-Value	0.03764	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXIX: Summary Statistics on CLTV Regression
Banks FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.6446	0.7313	-2.249	0.0329	*
Slope	0.9707	0.1774	5.472	8.6E-06	***
RMSE	0.3896		F-statistic	29.94	
R-Squared	0.5258		P-Value	8.6E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 740 – 780

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.8589	0.7087	-2.623	0.0142	*
Slope	1.0172	0.171	5.949	2.42E-06	***
RMSE	0.5547		F-statistic	1.088	
R-Squared	0.03872		P-Value	0.3062	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Banks FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.5278	0.6942	-2.201	0.0365	*
Slope	0.9631	0.1721	5.597	6.16E-06	***
RMSE	0.3849		F-statistic	31.33	
R-Squared	0.5371		P-Value	6.16E-06	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Non-Bank FICO: 780+

	Estimate	Std. Error	T-Value	Pr(>|t|)	
(Intercept)	-1.6624	0.6695	-2.483	0.0195	*
Slope	0.9936	0.1655	6.005	2.09E-06	***
RMSE	0.5639		F-statistic	0.1749	
R-Squared	0.006436		P-Value	0.6791	

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure XXX: Classification of Banks and Shadow Banks

Banks	Shadow Banks
Ally Bank	Amerisave Mortgage
Bank of America	Cashcall Inc
BOK Financial	Guaranteed Rate Inc
Branch Banking and Trust Company	Homeward Residential
Capital One	Movement Mortgage
Citibank	Quicken Loans
Citimortgage	Academy Mortgage
Colorado FSB	AmCap Mortgage LTD
Everbank	American Neighborhood Mtg
FHLB Chicago	American Pacific Mortgage
Fidelity Bank	Amerifirst Financial Corp
Fifth Third Mortgage	Amerihome Mortgage
First Republic Bank	Ark-LA-TEX Fin Svcs.
Flagstar Bank FSB	Bay Equity Shadow
Fremont Bank	Broker Solutions
Homestreet Bank	Caliber Home Loans
HSBC Bank	Chicago Mortgage Solutions
JPMorgan Chase	CMG Mortgage
MB Bank	Ditech Financial
Metlife Home Loans	Fairway Independent Mortgage
Mortgage Stanley Private Bank	Franklin American Mortgage
MUFG Bank	Freedom Mortgage
Navy FCU	Greenlight Financial
NY Community Bank	Guild Mortgage
PNC Bank	Homebridge Financial Services
Redwood Credit Union	Impact Mortgage
Regions Bank	LoanDepot.com
Union Savings Bank	Mortgage Research Center
US Bank	Nationstart Mortgage
USAA FSB	Newday Financial
Wells Fargo Bank	Pacific Union Financial
	PennyMac Loan Services
	PHH Mortgage
	Plaza Home Mortgage
	Primary Residential Mortgage Inc.
	PrimeLending
	Primelending Plainscapital
	Prospect Mortgage
	Provident Funding
	Sierra Pacific Mortgage
	Sovereign Lending Group
	Stearns Lending
	Stonegate Mortgage
	Suntrust Mortgage
	Sunwest Mortgage
	Walker and Dunlop