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Essays on Mortgage Refinance

By

Yunbo Liu

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Nancy Wallace, Chair
Professor Benjamin Handel
Associate Professor Amir Kermani
Assistant Professor Matteo Benetton

Spring 2025

Essays on Mortgage Refinance

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Abstract

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This thesis explores how households make financial decisions and how financial intermediaries interact with households by investigating mortgage refinance choices. Initially, the thesis concentrates on the mortgage market for low-to-moderate income households who are especially prone to financial market frictions. After finding evidence of significant welfare loss, I explore channels from both the household side and financial intermediary side that explain these frictions. Subsequently, the thesis explores the behavioral biases that explain prevalent inaction in mortgage refinancing and conducts analysis on the use of lender credits. Given the importance of the mortgage refinance channel in the efficiency of monetary policy pass-through, the final part of the thesis explores household interest rate expectation biases and their implications on mortgage refinance choices.

Frictions in mortgage refinance choices exist not only in whether or when to refinance, but also in the type of mortgage households refinance into. Chapter 1, **Frictions in Mortgage Refinance Choices: Evidence from Federal Housing Administration Mortgages** studies frictions involved in mortgage refinance product choices. Using loan level data, I find that about 40% of FHA-to-FHA refinancers during 2009-2020 could have saved approximately $110 (10%) per month and $2,957 upfront by switching to a conventional Government Sponsored Enterprise (GSE) loan at refinance. Minority and low-income FHA borrowers are less likely to make the switch. These borrowers continue to pay an avoidable mortgage insurance premium (MIP), even though their property value appreciation are qualified for a GSE loan, since they do not reassess their property value when refinance. I then examine both demand-side and supply-side channels to explain these frictions. On the demand side, I find that property value information updates can reduce refinance frictions. Households who received an updated property tax bill are more likely to refinance to a GSE loan. On the supply side, I demonstrate that lenders may prefer FHA-to-FHA refinance loans due to higher upfront fees and securitization revenue. An exogenous increase in lenders' revenue (cost) of originating FHA loans results in less (more) refinance to GSE mortgages.

Households often make costly and systematic errors in mortgage refinancing, either by refinancing too early or delaying to the point of inaction. Chapter 2, coauthored with Mingzi Niu, **Mortgage Refinance under Present Bias: Evidence From the Use of Lender Credits** examines how present bias may explain these refinancing frictions. We develop a theoretical framework that incorporates present bias into refinancing decisions and derive closed-form solutions for optimal refinancing thresholds. Our model indicates that present-biased borrowers require larger interest rate drops to refinance and are more sensitive to changes in upfront costs. We further test our model in the setting of lender credits. Using U.S. mortgage data from 2010-2019, we identify lender credit usage through FHA loan features. We find borrowers using lender credits refinance earlier in interest rate cycles but achieve smaller rate reductions compared to those who pay closing costs out of pocket.

The efficiency of monetary policy pass through into household sector rely on households forming interest rate expectations in alignment with policy goals. However, evidence shows household are subject to significant bias. In Chapter 3, coauthored with Hao Pang, **Mortgage Rate Expectations and Refinance Choices**, we use survey data to show evidence of biases in mortgage rate expectations. We find that professional forecasters often overreact to interest rate changes, while households tend to underreact. These frictions lead to mortgage refinance mistakes. Households with lower property values tend to refinance too early in declining rate environments, while households with higher property values often wait too long, missing optimal refinancing opportunities. These results contribute to the understanding of household interest rate expectation formation and household borrowing decisions.

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Chapter 1

Frictions in Mortgage Refinance Choices: Evidence from Federal Housing Administration Mortgages

1.1 Introduction

Mortgage refinance has been a key channel for transmitting monetary policy to the household sector. Frictions in mortgage refinance have been widely discussed in the literature (e.g., Keys et al., 2016; Di Maggio et al., 2017; Andersen et al., 2020). However, most of the literature focuses on how households decide *whether* or *when* to refinance, based on changes in interest rate. In this paper, I investigate a new aspect of refinancing decisions, namely, the choice of mortgage refinance products. I emphasize that households should also refinance based on changes in their risk profile. Specifically, households should decide which type of mortgage loan they refinance to, based on changes in their property value. There are significant frictions in this decision as well, causing borrowers to overpay on their mortgages.

Federal Housing Administration (FHA) mortgages are particularly well-suited for studying frictions involved in refinancing product choices. FHA charges borrowers higher risk premium through mortgage insurance, to compensate the default risk associated with low down payment. When FHA mortgage borrowers refinance, they have the option to switch products to reduce their risk premium by removing mortgage insurance. FHA mortgages have comprised 28% of all owner-occupied home mortgages—totalling $1.3 trillion—from 2009 to 2017, and are more prominent for minority, low-to-moderate income and first time home-buying households.[1] Despite their prominence, the FHA market is less studied in the research literature compared to the conventional mortgage market, particularly regarding

[1]https://www.clevelandfed.org/newsroom-and-events/publications/economic-trends/2015-economic-trends/et-20150414-fha-lending-rebounds-in-wake-of-subprime-crisis.aspx

how FHA borrowers' mortgage choices differ from other borrowers.

My research specifically answers the following questions: What product do FHA borrowers choose to refinance to, when interest rates and property values change, given that they have the option to switch from FHA to Government-sponsored Enterprises (GSE) mortgage? What are the factors that explain FHA refinance product choices, and how can regulators respond to reduce these financial market frictions?

To answer these questions, I examine the population of FHA borrowers who purchased single-family residential property after 2009 and subsequently refinanced their mortgages before 2020. In this sample period, 60% of FHA borrowers refinanced to a new FHA loan, while 40% of FHA borrowers switched to a GSE loan. The decision to stay with an FHA mortgage or switch to a GSE mortgage can significantly impact monthly payments. Refinance to a conventional GSE loan removes the Mortgage Insurance Premium (MIP), which adds about 1% to the mortgage rate, and has to be paid for the entire lifetime of the mortgage. To be qualified for the switch, borrowers need to have at least 20% equity in the property at the time of origination. This loan-to-value (LTV) requirement can be achieved through home value appreciation. On the contrary, FHA-to-FHA refinances are conducted through the FHA Streamline Refinance program, which has a "no reassessment" feature intended to protect underwater households. Since properties were not reassessed, the LTV used in FHA-to-FHA refinances does not reflect changes in the property value. This results in FHA borrowers staying with FHA mortgages at refinance may overpay on their mortgage rate, because they overpay on their risk premium.

These frictions in FHA refinance choices are substantial, resulting in sizeable costs to FHA borrowers. Using a hedonic model to predict counterfactual property equity growth, I find that 40% of the FHA borrowers who refinanced to a new FHA loan were eligible for a GSE loan. Switching to GSE loans at refinance would save them on average $110 (10%) monthly and $2,957 upfront on mortgage payments by eliminating the MIP. This represents 1.7% of the household income of an average FHA borrower. I also find that these frictions in mortgage choices were more prevalent among minority and low-income borrowers. Black FHA borrowers are 12% less likely to refinance to GSE loans when eligible. FHA borrowers with income in the lowest quartile of the population are 23% less likely to refinance to GSE loans when eligible.

To understand these frictions, I specifically examine two main channels from the demand side and the supply side. From the demand side, frictions may arise if households are not aware of their property value change. Property value is the key factor determining the eligibility for FHA-to-GSE refinance. To test how property value information affects refinance choices, I examine the exogenous shock of tax reassessment events in states where property taxes are infrequently updated. I find that after receiving a new property tax bill indicating the increase of their property value, eligible households are 12% more likely to refinance their FHA mortgage to a GSE mortgage.

From the supply side, I examine the variation in FHA refinance choices across lenders, and how FHA refinance choice outcomes change when lenders' incentives change. Lender fixed effects explain about 10% variation in FHA refinance choices. FHA borrowers are 13%

less likely to refinance to a GSE loan when they refinance with a nonbank lender. I further discuss potential incentives for lenders to prefer originating FHA-to-FHA refinance loans than FHA-to-GSE refinance loans. Lenders charge higher upfront origination fees to FHA refinance loans. FHA refinance loans can be sold at a higher price in the secondary market. To show the causal relationship between lender incentives and FHA refinance choices, I tested how two policy shocks affected FHA refinance choices, through their effects on lenders' revenue and cost of originating FHA loans. Specifically, when new regulations granted FHA mortgages preferred status in Liquidity Coverage Ratio calculations, affected eligible FHA borrowers became less likely to refinance to GSE loans. The usage of the False Claim Act against bank lenders, increased the probability for affected eligible FHA borrowers to refinance to a GSE loan.

My research contributes to several strands of the literature. First, it extends the classic literature on mortgage choice by incorporating risk premium (mortgage insurance) as an additional factor. Previous work by Stanton (1995), Stanton and Wallace (1998), and Agarwal et al. (2013) provides frameworks to analyze optimal mortgage choice based on assumptions about interest rate dynamics and expected mortgage rate distributions. I argue that factors determining risk premium (for example, LTV) should also enter the choice function. Especially in the context of the FHA mortgage market, because mortgage insurance premium costs are a significant component of mortgage costs.

Second, my research provides new empirical evidence of households deviating from optimal mortgage refinance choices, complementing work by Keys et al. (2016), Agarwal et al. (2016) and Andersen et al. (2020). Keys et al. (2016) documented the fact that about 20% of households failed to refinance and save $160 per month. Andersen et al. (2020) used Danish data to show there is a psychological cost related to inaction behavior in mortgage refinance, and the degree of inaction is related to multiple demographic characteristics including age, education, and wealth. My research shows that households still leave money on the table when they choose to refinance, due to the additional feature in FHA mortgage refinance choice mentioned above. I also find demographic characteristics are correlated with this specific suboptimal choice.

Third, my research examines the role of lenders' strategies in the FHA market, contributing to the literature on the industrial organization of financial intermediaries. Kim et al. (2018), Buchak et al. (2018), Jiang (2019), and Benetton et al. (2021) discuss various aspects of lender competition in the mortgage market, including warehouse lending channels, cannibalization effects, fintech technology, and competition for profit on different dimensions of financial product features. I illustrate that the mortgage refinance choice outcome is correlated with lenders, especially when financial products are more complicated, when borrowers have less information, and when lenders have more market power.

Finally, my research contributes to the discussion on the heterogeneity of macro policy pass-through. Previous work by Wong (2019), Beraja et al. (2019), Auclert (2019), Di Maggio et al. (2020), Berger et al. (2021), and Zhang (2022) examine the refinance channel for the transmission of monetary policy and its heterogeneity with respect to demographic characteristics and regional variation. Wong (2019) studies age-based heterogeneity in consumption

effects. Di Maggio et al. (2020) find that central bank MBS purchases increase refinancing activity and aggregate consumption. Berger et al. (2021) show how refinancing decisions depend on both current interest rates and their expected path. Benetton et al. (2021) discuss how lenders react to a reduced interest rate by increasing mortgage fees and how this impacts the welfare allocation between borrowers and lenders. While previous research focuses on the decision of *whether* to refinance, I show that given people have refinanced, there is still substantial heterogeneity of payment savings, because households still need to decide *what* to refinance to. Thus interest rate policies may create mortgage payment gaps in frictional financial markets.

The rest of this paper proceeds as follows. Section 1.2 introduces the institutional background of the FHA mortgage market, the choice problem of borrowers and the dataset. Section 1.3 presents stylized facts about FHA refinance choices and quantifies suboptimal decision patterns. Section 1.4 examines the robustness of the estimation and heterogeneity of my results. Section 1.5 examines the demand-side factors, focusing on how information frictions influence borrowers' decisions. Section 1.6 investigates the supply-side factors, focusing on how lender incentives influence refinance outcomes. Section 1.7 discusses policy implications and concludes.

1.2 Institutional Background of FHA Mortgages

FHA Mortgages

Established under the U.S. Department of Housing and Urban Development (HUD) by the National Housing Act of 1934, the Federal Housing Administration (FHA) aims to increase homeownership accessibility, particularly for first-time and low-to-moderate income buyers, by insuring mortgages with more lenient credit requirements. As the subprime mortgage market collapsed during the 2008 financial crisis, FHA-insured loans experienced a surge in popularity. FHA mortgages account for 28.1% of total home purchase loan amount (32.6% of loan count) in 2009, according to U.S. Department of Housing and Urban Development calculations. [2] Over the last decade, FHA loans consistently represent over 20% of the mortgage market. 49.7% Low-to-Moderate Income (LMI) borrowers (income less than 80% of area median income), and 41.9% borrowers under 35 use FHA mortgages to buy their first home.[3] The FHA's unique institutional settings make it a particularly intriguing area of study, offering insights into government intervention in housing finance and household mortgage decisions for marginal homebuyers.

The LTV requirement for a conventional GSE loan is 80% (20% down payment).[4] FHA loans offer more lenient requirements compared to conventional mortgages. Applicants can

[2]https://www.hud.gov/program_offices/housing/rmra/oe/rpts/fhamktsh/fhamktqtrly

[3]https://www.urban.org/sites/default/files/2023-07/Housing-Finance-At-A-Glance-Monthly-Chartbook-July-2023.pdf

[4]Borrowers can also get a GSE loan with LTV greater than 80% by purchasing private mortgage insurance. Recent industry reports suggest that FHA mortgages are cheaper for borrowers with LTV over 90%,

qualify with a LTV of up to 96.5% (3.5% down payment). Additionally, the minimum credit score for FHA-insured mortgages is 500, significantly lower than the 620 typically required for conventional GSE loans. However, for the majority of households, the down payment requirement tends to be the primary limiting factor rather than the credit score threshold.

To compensate for the increased default risk associated with high LTV, the FHA charges a risk premium in the form of mortgage insurance premium. This mortgage insurance premium is composed of two parts: an upfront mortgage insurance premium (UFMIP) and a monthly mortgage insurance premium (MIP). Both UFMIP and MIP are uniform to all FHA borrowers across the U.S. applying in the same period. This mortgage insurance premium is required for the entire lifetime of the mortgage, unless the FHA loan is prepaid. The level of the insurance premium has changed several times in the past decade, with an increase right after the 2008 financial crisis and a decrease recently (See Table A.1). [5]

FHA Refinance Choice

The choice problem for FHA borrowers can be more complicated than for conventional GSE borrowers. As illustrated in Figure 1.1, there are four components that determine the rate a mortgage borrower actually pays.

$$P_{i,j,t,m} = R_t + Q_{i,m,t} + I_{i,m,t} + \eta_{i,j}$$

Where $P_{i,j,t,m}$ represents the total mortgage rate paid by borrower i for mortgage product m originated by lender j at time t. R_t is the baseline long-term rate, which reflects the funding cost for lenders to originate a mortgage. This usually depends on macroeconomic policy, such as, the change in the Federal Funds Rate and the effect of RMBS purchasing programs. In this context, R_t is approximately the same across lenders. $Q_{i,m,t}$ is the risk premium associated with borrower, usually a function of credit score, LTV ratio and Debt-to-Income (DTI) ratio. A commonly used pricing function is the Loan Level Price Adjustment table (LLPA) from the Federal National Mortgage Association (FNMA) and the Federal Home Loan Mortgage Corporation (FHLMC). $I_{i,m,t}$ is the mortgage insurance premium that applies when the LTV is greater than 80%. This insurance protects the mortgage security investors in the event of default. For FHA mortgage this will be the UFMIP and MIP discussed in the previous section. For GSE mortgage this will be the price of private mortgage insurance. Finally $\eta_{i,j}$ reflects the mark-up charged by the lender. This term typically depends on the market structure of the local lenders, as well as the shopping behavior and bargaining power of the borrowers.

In the literature studying mortgage refinance choices, the choice problem of a mortgage borrower is a function of the mortgage rate of the previous loan and the mortgage rate

after comparing rates and fees, and almost all of the borrowers in my sample fall in this LTV range, thus the competition between private mortgage insurance market and the FHA mortgage market should not be a concern for the scope of this paper.

[5] On February 22, 2023, the U.S. Department of Housing and Urban Development (HUD) announced a 30 basis points reduction in the FHA's annual mortgage insurance premium.

at the time of refinance, for example in Agarwal et al. (2013). Previous studies typically estimated this rate difference using only changes in the Federal Funds Rate or Primary Mortgage Market Survey (PMMS) rate, which captures only changes in the baseline R_t. The borrower's choice function would be:

$$V_t(r_0, i) - V_t(r_t, i) - c_{i,t} \geq \delta_{i,t}$$

$V_t(r_0, i)$ represents the discounted value of all remaining future mortgage payments for individual i at time t when the existing mortgage rate is r_0. $V_t(r_t, i)$ represents the discounted value of all future mortgage payments for individual i at time t if they refinance the existing mortgage to a new mortgage at rate r_t. The benefit of refinance minus the cost of refinance $c_{i,t}$ should be greater or equal to a certain threshold $\delta_{i,t}$ for individual i for the mortgage refinance to happen.

While this model effectively approximates refinancing choices for conventional GSE mortgages, FHA borrowers face a more complicated choice:

$$V_t(R_0 + Q_0 + I_0, i) - V_t(R_t + Q_t + I_t, i) - c_{i,t} \geq \delta_{i,t}$$

Where

$$\begin{aligned} Q_0 + I_0 &= f(FICO_0, LTV_0) \\ Q_t + I_t &= f(FICO_t, LTV_t) \\ c_{i,t} &= c^r_{i,t} + c^I_{i,t} \end{aligned}$$

Compared to the previous case, the new mortgage rate change depends on both change in long term risk free rate and borrower specific risk premium, which is a function of the borrowers' credit score and LTV. The upfront cost of refinance has the component of regular processing cost and UFMIP cost if refinance to a new FHA mortgage. It's safe to assume this part is small enough to ignore in most of the conventional GSE refinance cases, but the magnitude of mortgage payment and upfront cost reductions from the change in risk premium can be substantial for FHA refinances.

The major friction in overpaying FHA mortgages after refinance is from the MIP. An FHA borrower who qualifies for a conventional GSE mortgage should refinance to a GSE mortgage and avoid the continued payment of the FHA MIP. The primary factor typically constraining FHA borrowers is the LTV, which is closely related to the equity amount on their home balance sheet. In the absence of a substantial cash influx, it generally takes approximately 10 years for a FHA mortgage, initially at 96.5% LTV, to accumulate 20% equity through amortization from monthly payments alone. It is crucial to note that amortization is not the sole mechanism by which homeowners can build equity. Property value appreciation, particularly common in a thriving economy, also contributes to lowering the LTV. The FHA program was designed to enable low-to-moderate income households to invest in real estate with lower entry costs. These homeowners should benefit from property value growth, not only through capital gains in real estate value, but also through reduction in their

borrowing costs. Specifically, FHA borrowers who experience enough property value growth may become eligible to refinance their FHA mortgages into conventional GSE mortgages. This switch result in considerable long-term savings by eliminating MIP.

The FHA Streamline Refinance Program

When borrowers refinance, are they not required to reassess their property value? Not for FHA-to-FHA refinances. One important feature of FHA-to-FHA refinances is the FHA Streamline Refinance Program. This program is designed to facilitate the refinance of an existing FHA-insured mortgage, by waiving some documentation requirements, including reassessment of the property value. There are several rules that apply to FHA streamline refinances. First, the FHA loan must be originated at least 6 months ago. Second, the FHA loan must be current (not delinquent). Third, regular cash out refinance can not be taken through the FHA Streamline Refinance program, since there is a $500 cap on cash out amount.

A prominent feature of the FHA streamline refinance program is that it waives the appraisal requirement. This provision was purposefully designed to protect underwater borrowers during economic downturns, enabling them to refinance their FHA loans even with declining property values. Under this program, borrowers use the original property value from the time of purchase for the new loan, irrespective of current market conditions. This mechanism also serves the countercyclical nature of FHA lending by mitigating further downward pressure on the housing market that could result from FHA borrowers defaulting and selling their properties.

The borrowers have to pay the upfront mortgage insurance premium (UFMIP) again for the new FHA mortgage under FHA streamline refinance program. Even though there exists a "UFMIP refund", the refund benefit diminishes fast over time. Figure A.2 illustrates the UFMIP refund schedule as a function of time since origination of the FHA mortgage. FHA borrowers only get 10% of the UFMIP back if they refinance 32 months (median time to refinance) after the initial loan was originated.[6]

In summary, for FHA borrowers who meet the eligibility criteria for GSE mortgages, the refinance choice has significant financial implications. Opting for an FHA-to-FHA refinance through the FHA streamline refinance program, while seemingly more convenient, generally results in higher overall costs compared to refinance to a GSE loan with a new property appraisal. This cost differential comes in two primary ways: first, in the immediate UFMIP, and second, in the long term through the monthly MIP.

Data

My analysis compares borrowers' credit status and mortgage loan characteristics between home purchase and refinance. This information is from Black Knight McDash mortgage

[6]See https://www.hud.gov/sites/documents/4155-2_7.pdf for details about UFMIP refund.

servicing data (hereafter referred to as the McDash data). The McDash data is a comprehensive database of mortgage performance and servicing. It collects information from mortgage servicers and covers about 80% of mortgages in the U.S., providing information on loan amount, interest rates, credit scores, property values, LTV, product types and other information. The McDash data also tracks the performance of each mortgage monthly until the mortgage is prepaid or foreclosed.

One limitation of the McDash data is that it is anonymized at the loan level. When a borrower refinances and prepays a loan, researchers can not identify which new loan prepays the old loan. To connect the refinance loan with the prepaid loan, I merged the McDash data with the ATTOM recorder data following Bartlett et al. (2021), by exploiting overlapping variables with a statistical-learning algorithm. The ATTOM data collects data from local recorder and assessor offices, provides transaction records of each property, as well as lender identities. The ATTOM data also provides information on property characteristics that are essential to estimate pricing models for counterfactual market price, including location, number of bedrooms and bathrooms, square footage, year the property was built and other variables.

To enrich my analysis, I also incorporated additional borrower characteristics data from HMDA, dynamic credit score and income from Equifax, MBS price estimate from TRACE and eMBS. The Home Mortgage Disclosure Act (HMDA), mandated by federal law since 1975, requires financial institutions to maintain, report, and publicly disclose loan-level information about mortgage applications and decisions. HMDA covers approximately 90 percent of US mortgage originations. It contains mortgage information and location that enables researchers to merge it with the above datasets. This additional borrower information—borrower race, gender and income—is used in my analysis. Equifax is one of the three commonly used credit bureaus in the U.S. They provide and maintain their proprietary Equifax Credit Score for each borrower. Equifax updates credit scores monthly, providing a dynamic view of consumer credit status.

1.3 Empirical Strategy

Sample Construction

I use the population of households who purchased a single family residence house using FHA mortgage starting from 2009. This is the year right after the Great Financial Crisis and FHA mortgages become a major choice for low-to-moderate income households, due to the collapse of private label securitization market for subprime loans. I then restrict the population to every borrower who refinanced their FHA mortgage by the end of 2020. These households already overcame the inertia of refinance, worked with their lender and successfully got approved for the refinance mortgage. Focusing on borrowers who already refinanced allows me to make minimal assumptions on both the credit eligibility and refinance decision process. Borrowers' credit status at the time of refinance are observed in the data. These households

also clearly care about reducing their mortgage payments. From 2009 to 2020, I end up observing 522,561 FHA borrowers who refinanced their mortgage in the McDash-ATTOM merged data. This is about half of total FHA refinances recorded, due to sample losses during the merging process. The distributions of initial FHA loan features (interest rate, loan-to-value, FICO score and property value at origination) are similar between the final sample and the sample dropped due to incomplete information (see Table A.1).

Actual Refinance Choices

As mentioned in the previous section, the main choice these FHA borrowers have to make is whether to do an FHA streamline refinance and stay with an FHA mortgage, or do a reassessment of their property and refinance to a conventional GSE mortgage, and remove their MIP. Among all the 522,561 FHA borrowers who refinanced their mortgage during 2009 and 2020, 216,080 refinanced to a GSE loan and 306,481 refinanced to an FHA loan.

Table 1.1 compares the summary statistics of the variables used in my analysis between the two groups. Panel A summarizes the FHA borrowers who refinanced to a GSE mortgage and Panel B summarizes the FHA borrowers who refinanced to a new FHA mortgage. Table 1.1 presents the following stylized facts.

First, both FHA-to-FHA and FHA-to-GSE groups experience a drop in mortgage payment and interest rate after refinance. This indicates that borrowers generally benefited from lower monthly payments after refinancing, consistent with people refinancing optimally. It's also important to point out that we see FHA-to-FHA refinances seem to save more on mortgage payments. This is because that a lot of the FHA-to-GSE refinances increased their loan amount at refinance to take a large amount of cash out. We can think of the additional mortgage payments for some FHA-to-GSE refinances as additional borrowing using their house as a collateral.

Second, the credit scores of FHA-to-GSE and FHA-to-FHA groups are similar at the time of purchase and refinance, with the FHA-to-GSE group having a slightly higher FICO score. Specifically, the median FHA-to-FHA refinancier have a credit score better than the 25 percentile FHA-to-GSE financier. This means these FHA-to-FHA will pass the FICO score requirements for refinancing to a GSE loan. Figure A.6 further illustrates the distribution of credit score at refinance, I will discuss credit score eligibility in later sections.

Third, FHA-to-FHA refinance happens faster than FHA-to-GSE refinance. It takes on average 35 months for an FHA loan to refinance to an FHA loan, but it takes on average 47 months for an FHA loan to refinance to a GSE loan.

Finally, the group of FHA-to-FHA refinance and FHA-to-GSE refinance exhibit similar property value at origination. But their property values on refinance documents at the time of refinance are dramatically different. Both groups start from average property value at about $250,000, but at the time of refinance, the FHA-to-FHA group on average shows 5% property value growth, while the FHA-to-GSE group experiences 20% property value growth. However, this property value growth of FHA-to-FHA refinance group does not reflect the actual property value growth and equity positions of these borrowers. As mentioned in

Section 1.2, FHA streamline refinance do not conduct a reappraisal and cannot take cash out, so the staleness of property value is mechanical and inaccurate.

Constructing Counterfactual Property Value Growth

Figure 1.2 plots the property value growth over total months from original FHA purchase loan to refinance. No matter how long has passed since the property was purchased, FHA borrowers who refinanced their mortgage through the FHA streamline refinance program report almost the same property value on their mortgage refinance application. While the group of FHA borrowers who refinanced their FHA mortgages to GSE mortgages report a substantial property value growth consistent what people would expect during the booming housing cycle of 2009-2020.

This result is mechanical, but what the property values would be for the FHA-to-FHA refinance borrowers, if they actually go through a reappraisal process? I construct a measure of property value growth using a hedonic pricing model with available data:

$$\ln(P_i) = \alpha + \beta X_i + \gamma N_i + \epsilon_i$$

Where P_i is the price of property i; X_i is a vector of characteristics of property i, including square footage, number of bedrooms and bathrooms, and year when the property was built. N_i is a vector of controls at the local level, specifically census tract by year fixed effects to control for neighborhood characteristics. ϵ_i is the error term. I first use the FHA-to-GSE refinance property value as left-hand side variable to estimate the model. I then predict the log property value for the FHA-to-FHA refinance properties. The underlying assumption is that properties with same characteristics and in the same location should on average experience the same amount of property value growth over the same period of time.

Figure 1.3 shows the comparison between property value growth on refinance application and property value growth I constructed using hedonic model for both the FHA-to-FHA and FHA-to-GSE refinance groups. Under the assumption that property value should be predictable by a hedonic model, the property value growth is almost identical between the two groups. The the two groups show dramatic differences in property values on refinance application record, if the FHA-to-FHA refinance group borrowers got an reappraisal of their property, on average they should experience the same amount of property value growth as the FHA-to-GSE refinance group. More importantly, these borrowers will find themselves eligible for an FHA-to-GSE refinance and remove the MIP. I consider alternative measures of counterfactual property growth in the Section 1.4.

Quantifying the Magnitude of Suboptimal Choices

After constructing the counterfactual property value growth, I calculate the proportion of FHA borrowers who refinanced to another FHA loan but were potentially eligible for a GSE loan. I then quantify how much money they could have saved by switching to a GSE loan.

In the baseline results, I assume the property value increase needs to be larger than 16.5%, which would make an FHA loan of 96.5% LTV eligible for a GSE loan with 80% LTV, even without any amortization happening between purchase and refinance. The FICO score at refinance should be greater than 620, the usual cutoff applied by GSE underwriters.

I then estimate the savings on mortgage payments if the identified eligible FHA borrowers actually make the switch. The results are reported in Table 1.2. 41% of FHA-to-FHA refinances would have been eligible for refinancing to a GSE loan. Figure 1.6 plots the histogram of estimated monthly and upfront savings if an eligible FHA borrower switched from an FHA streamline refinance to a GSE refinance. The mean and median savings from switching an FHA-to-FHA refinance to a FHA-to-GSE refinance are \$110 and \$100 dollars per month, which is about 1.7% of their household monthly income. They will also save the mean and median of \$2,957 and \$2,632 dollars from the upfront mortgage insurance premium cost.

This result is economically significant compared to the literature. In Keys et al. (2016), an average of \$160 per month potential savings was estimated for GSE borrowers who failed to respond to decrease in interest rates. In Andersen et al. (2020), Danish households missed DKK 2,700 (USD \$400) per year (\$33 per month) and 58 basis points of household income in mortgage savings by not refinancing optimally. Even if the credit score and property value appreciation constraints are restricted to a very strict range, the data still identify more than 20% of the FHA borrowers who refinanced to an FHA loan during the sample period, leaving a large amount of money on the table. The savings is also comparable to the automatic refinance scheme estimated by Gerardi et al. (2021), where the authors estimated the average equity growth for FHA borrowers is \$23,000 and refinance can save about \$93 on mortgage payments.

To quantify total overpayment on suboptimal FHA refinance decisions, we need to consider how long borrowers continue to pay their refinanced mortgage before conducting a second refinance or moving out. Refinance at a time when the mortgage rate is low usually means that the interest rate level is unlikely to decrease further within a few years. In my sample during 2009 to 2019, 62% FHA borrowers who refinanced to a new FHA mortgage continued to pay the same refinance mortgage until the end of 2019. Only 16.7% FHA borrowers who refinanced to a new FHA loan conduct a second refinance. Even for those who refinanced again, the average time they keep paying their first refinance loan is longer than the average lifetime of an FHA loan, with a mean value of 44 month and a median value of 40 months. Thus, a lower bound estimate of lifetime overpayment on FHA MIP for an average FHA borrower who suboptimally refinanced to a new FHA mortgage would be \$7,797.

Figures 1.4 and 1.5 illustrate the count and share of refinance choices made by FHA borrowers. These are categorized into: 1) FHA-to-GSE refinances; 2) FHA-to-FHA refinances eligible for FHA-to-GSE refinance; and 3) FHA-to-FHA refinances not eligible for FHA-to-GSE refinance. Figure 1.4 shows the decomposition by the year when refinancing occurred, while Figure 1.5 shows the decomposition by quarters since home purchase to refinance. The figures demonstrate that during the years when refinance happens more often

due to low mortgage rates, there are also more FHA borrowers experience suboptimal refinance product choices. The proportion of FHA-to-FHA refinances that were eligible for FHA-to-GSE refinance slightly increased over the sample period. The trend in the first few years is consistent with the fact that property value growth is highly correlated with tenure in the property. So the longer an FHA borrower stays in their house, the more home equity they accumulate over time, and the more likely they are eligible to refinance to a GSE mortgage and reduce their mortgage payments. After a few years of residence, most people have already accumulated more than enough home equity to make them eligible to refinance to a GSE loan, in these situations other factors including individual specific credit shocks and influence from lenders dominate.

1.4 Robustness and Heterogeneity

In the previous section, I estimated the proportion of FHA borrowers eligible for GSE refinancing and quantified their potential savings upon transitioning to a GSE mortgage. This estimation is based on counterfactual calculations of how much an FHA borrower's property value would increase following a reappraisal, which is a key factor in determining the likelihood of approval for a GSE refinance loan. In this section, I will address potential concerns regarding the robustness of this estimation. Specifically, I will present results using alternative measures of property value, credit score, and income. Furthermore, I will explore the heterogeneity in FHA refinance choices across various demographic groups.

Robustness of Property Value Estimate

First, there are concerns about the hedonic model method used to construct counterfactual property value growth. If FHA-to-FHA refinances occur without corresponding FHA-to-GSE refinances in the same neighborhood and with similar property characteristics, the estimated property value growth will closely approximate the average FHA-to-GSE refinance property value for a similar property in a different neighborhood. This might result in an upward bias for properties in less developed neighborhoods or those with certain unpopular characteristics. Additionally, while the hedonic pricing method is commonly used in appraisal practices, not all property appraisals follow this method.

To address these concerns, I use the Zillow Home Value Index as an alternative measure of property value growth. The results are shown in Figure A.4. There is a noticeable gap between the Zillow index changes for the FHA-to-FHA refinance group and the FHA-to-GSE refinance group, indicating that the aforementioned concerns exist. A proportion of the FHA-to-FHA refinance group may indeed reside in zip codes experiencing less property value growth.

Despite the Zillow estimates showing a gap in property value growth between FHA-to-GSE and FHA-to-FHA refinance groups, most households experienced property value growth more than 16.5%, which makes them eligible to refinance to a GSE loan. Using the Zillow

Home Value Index as the specification to estimate the proportion of FHA-to-FHA borrowers eligible for GSE loan refinancing does not alter the main conclusion.

Second, concerns have been raised about FHA borrowers potentially not maintaining their properties adequately. There might be characteristics not reflected in the assessor data that are endogenous to a borrower's decision not to get an appraisal, such as outdated systems, appliances, and interiors. To address this concern, I examine the subset of the FHA-to-FHA refinance group that sold their houses before the end of my sample period, comparing their sales prices to their property values at the time of refinancing.

The results are presented in Figure A.5. FHA-to-FHA refinanced households later sold their houses at significantly higher prices than their purchase values. On average, property values increase by more than 20% when they resale on the market. This growth far exceeds what is reflected in the FHA Streamline refinance profile.

This finding provide strong evidence that the selection of FHA borrowers who skip a home value appraisal and refinance to another FHA loan is unlikely to be explained by poor property maintenance. The significant appreciation in property values, even within this group, indicates that these homeowners are indeed maintaining their properties to a standard that supports considerable value growth.

Robustness of Credit Score and Income

Additional concerns about the eligibility to refinance to a GSE mortgage could be that the credit score reported on the FHA streamline refinance profile may not be accurate. Even though the credit score I observe in McDash updates at refinance, this may be subject to bias due to inaccurate reporting practices.

To validate the FICO score and income change between purchase and refinance loans, I use an alternative data source: Equifax. Equifax Credit Risk Insight Servicing Data provides monthly panel of credit scores (Vantage Score 3.0) and income estimate. This is a separate source of borrowers' credit status. Figure A.9 and Figure A.10 plots the binscatter of McDash credit score collected at origination and refinance, as well as McDash credit score collected at refinance and Equifax credit score at refinance. The credit score is updated from origination to refinance. The two credit score measures closely track each other. Figure A.7 shows the distribution of FICO score for FHA-FHA refinanciers and FHA-GSE refinanciers in Equifax. Similar to the result using McDash data, over 80% FHA-to-FHA refinances have their Equifax reported credit score greater than 620 at the time of refinance, the minimum requirement for GSE loan, as well as the 10% percentile of all FHA-GSE refinanciers.

Concerns about the eligibility to refinance also come from income verification. As documented in DeFusco and Mondragon (2020), FHA streamline refinances require employment verification since 2009. Figure A.8 further confirm the eligibility from borrowers' financial status by showing the distribution of income growth during FHA borrowers first purchase and refinanced their mortgages. Most people experienced an increase in income, though the FHA-to-FHA group experienced less income growth than the FHA-to-GSE group. After

refinance mortgage payment will decrease, thus their Debt-to-Income ratios are unlikely to prevent them from getting approved for a GSE mortgage.

Heterogeneity

How do refinancing patterns vary across demographic groups? Are FHA borrowers' refinance choices correlated with their demographic characteristics? In this section I split my sample according to different criterion and show the heterogeneity of FHA refinance choices across different demographics.

I estimate the heterogeneous effect in the following regression explaining refinance choices:

$$y_{ijct} = \alpha + \beta\lambda_i + \gamma X_j + \xi_{ct} + \varepsilon_{ijct} \tag{1.1}$$

y_{ijct} is the dummy variable indicating refinance to GSE loan conditional on the hedonic model predicted property value increase larger than 16.5% and FICO score greater than 620 at time of refinance for borrower i, loan j in county c at time t. λ_i are borrower demographic characteristics, including borrower race (Black, Hispanic and Asian), gender and income quartile. X_j are loan level controls including FICO score, property value growth, loan amount, interest rate and time from purchase to refinance. ξ_{ct} is year-by-county fixed effects.

The estimates of coefficients of interests β are reported in Figure 1.7, holding other demographic and loan factors constant, eligible Black FHA borrowers are about 12% less likely to refinance to a GSE loan compared to non-Hispanic white FHA borrowers, and eligible Hispanic borrowers are 2% less likely to refinance to a GSE loan compared to non-Hispanic white FHA borrowers. Female borrowers are 1% less likely to refinance to a GSE loan when eligible compared to male borrowers. This heterogeneous pattern is consistent with the research documenting that Black and Hispanic homeowners pay significantly higher mortgage interest rates than white and Asian homeowners (Gerardi et al., 2023).

I then decompose the sample according to the quartile of their reported income. Households with incomes in the second, third and fourth quartile are 22%, 26% and 29% more likely to refinance to a GSE loan when eligible, compared to households with incomes in the lowest quartile. This result indicates these suboptimal mortgage refinancing decisions correlate with borrower income and other factors that affect household financial decisions, including financial literacy, access to financial service and experience in the financial market.

1.5 Demand Side Channel –Information Frictions

What factors explain this additional frictions in FHA mortgage refinance? In this and next section I provide evidence from both the demand and supply side of mortgage refinance frictions. On the demand side, information about how much property value has changed explains differences in the FHA mortgage refinance choice. I tested this hypothesis by using property tax reassessment as an information shock. I find that in the states where

the property tax basis is infrequently updated, the probability of eligible FHA borrowers refinancing to a GSE loan increases after they receive a new property tax bill. On the supply side, I show FHA refinance choice outcome is correlated with lenders. I discuss evidence on why lenders may prefer FHA refinance over GSE refinance, from the perspective of upfront fee, securitization revenue and other factors. Then I showed a shift in securitization revenue due to policy shock affects the propensity to conduct more efficient refinance.

Property value information plays a crucial role in FHA households' refinancing decisions, particularly when considering refinancing to a GSE loan. The importance of information is multifold: First, knowledge of increased property value helps FHA borrowers recognize their credit worthiness. They will understand their default risk decreases as their property value increase, thus borrowers should be eligible to save on their monthly mortgage payment. Second, increased property value may qualify borrowers for larger cash-out amounts, enjoying the weath effect of investing in the real estate market. Finally, even if borrowers initially pursue an FHA streamline refinance, accurate property value knowledge should prompt them to reconsider. Because they will notice that the property value on the application is much lower than their own knowledge of their home's value. Correcting this mistake naturally increases their propensity to refinance to a GSE loan. To investigate the impact of property value information on refinancing decisions, I conduct a test that exogenously separate households with and without the information about their property value, and compare their refinance choices using property tax reassessment as a natural experiment.

Set Up

In North Carolina, residential properties are reassessed every 4-8 years to calculate the new property tax basis. The time of tax reassessment is different across counties, and all properties in the same county are reassessed in the same year. This creates a natural staggered adoption of treatment, where some homeowners receive updated property value information earlier than others. The North Carolina Department of Revenue publishes this tax reassessment schedule. [7] Similarly in Ohio, property taxes are reassessed every 6 years. [8] For FHA borrowers residing in North Carolina and Ohio, upon receiving a new tax bill, they should update their information about their property value. This update in information will affect the refinance choice decision for FHA borrowers.

I implement a difference-in-difference method to compare the probability of an eligible homeowner refinancing to a GSE loan before and after receiving a new property tax bill.

$$y_{ict} = \sum_{\tau=t-3}^{t+3} \beta_\tau D_{it}^\tau + \gamma X_{it} + \xi_c + \eta_t + \varepsilon_{ict} \tag{1.2}$$

[7] North Carolina Department of Revenue. "County Property Tax Rates and Reappraisal Schedules." Available at :https://www.ncdor.gov/taxes-forms/property-tax/property-tax-rates/county-property-tax-rates-and-reappraisal-schedules

[8] Ohio Department of Taxation "Property Value Reappraisal and Update Schedule" https://tax.ohio.gov/government/real-state/reappraisal-and-triennial-update

The outcome variable y_{ict} is a dummy variable indicating whether the qualified household refinances their FHA loan to a GSE loan. Qualified is defined as the property value growth from purchase to refinance exceeded 16.5% according to the hedonic model in the previous section and credit score is above 620 at the time of refinance. D_{it}^{τ} is a dummy variable equal to 1 if year t is τ years before or after tax reassessment year. X_{it} are borrower control variables including credit score, property value and loan amount. ξ_c is the county fixed effect. η_t is the year fixed effect. The standard error is clustered at the the county level. The coefficient of interest is β_τ, which measures the difference, conditional on controls, in the outcome between treated and control borrowers τ years after the tax reassessment.

Result

I report year-by-year estimation results in Figure 1.8 and a single DIDs estimate that pool post-periods for the outcome in Table 1.3. After receiving a new property tax bill, households are on average significantly 12% more likely to refinance to a GSE loan when eligible, which is consistent with my hypothesis. The baseline probability of an eligible FHA borrower to refinance to a GSE loan is 43.3%. The effect increases over time following receipt of a new property tax bill, suggesting persistent information treatment effects.

Under this framework, the identifying assumption is that FHA borrowers who have not received an updated property tax bill in the 0-3 years period prior to the county level property tax reassessment event form a valid counterfactual group for FHA borrowers who are in the 1-3 years period after receiving the new property tax bill, conditional on control variables. This assumption implies that refinancing outcomes of the two groups would share parallel trends in the absence of property tax reassessments. The plot in Figure 1.8 supports this assumption, as the estimates before tax reassessment are not significantly different from zero, indicating similar trends between groups.

Robustness

An alternative explanation for refinancing decisions following property tax reassessment could be that households might experience financial pressure from higher property tax bills. So as a response, they choose to offset this increased tax burden by refinancing their mortgage. However, this alternative explanation does not weaken our main argument for two reasons. First, existing literature provides limited support for the effect of tax bill on refinance propensity. For example, Wong (2020) find no evidence of increased refinancing following increased tax bills. Second, while financial pressure from increased tax bills might explain a higher propensity to refinance, it does not explain why households would choose suboptimal refinancing products.

To further test this alternative channel, I separately analyze borrowers with higher credit scores and higher property values. Credit score and property value are highly correlated with income, and would indicate the borrower is less financially constrained, so that a sudden increase in property tax bill should not change their refinance choice much compared to

lower income groups. As reported in column (2) and (3) in Table 1.3, the results remain consistent for the high FICO score and high property value groups. Even among relatively higher-income FHA borrowers eligible for GSE loan refinancing, receiving a new tax bill significantly predicts higher GSE refinancing probability. So the concern about increased property tax payment change refinance choice is unlikely to replace the informational channel and explain FHA refinance choice.

The observed 12.2% increase result is the average treatment effect based on the population of FHA borrowers in North Carolina and Ohio, and should be a lower bound on the treatment effect on households who are actually compliers to this informational treatment. In this exercise, it is difficult to distinguish between households who are already aware of their property value increases and those who rely on property tax information to update their knowledge. From the result in the Table 1.3, the average treatment effect is smaller among households with high property value, suggesting that the treatment effect may be larger among households less attuned to property value changes.

1.6 Supply Side Channel –Lender Strategy

In complex financial decisions, such as mortgage refinancing, financial intermediaries play a critical role. Research by Allen et al. (2019) highlights the significant impact of search frictions on price discrimination, while Buchak et al. (2023) finds that fintech lenders leverage market power over recaptured borrowers by charging higher fees. As discussed in the previous sections, FHA refinance choices are particularly intricate and incur high information costs, creating an environment where lenders can substantially influence choice outcomes. In the pre-2008 FHA mortgage market, Woodward and Hall (2012) documented that borrowers overpaid lenders at least $1,000 in Yield Spread Premium. The Yield Spread Premium was banned in 2010 and no longer applies to the FHA mortgage market in my analysis. But can suboptimal FHA refinance choices discussed in this paper be partially attributed to lenders' influence?

Anecdotal evidence supports this argument. The Consumer Financial Protection Bureau (CFPB) maintains a database of consumer complaints regarding household financial products and services. [9] Multiple FHA borrowers have filed complaints indicating that their failure to refinance to a GSE mortgage was influenced by their lenders. For example:

> On XX/XX/2019 I was contacted by Caliber Home Loans to refinance, the only product offered was a FHA streamline refi... I come to find out that this was not the best option for me. The agent failed to explore all the refinancing options available to me. Since this process lacks an appraisal and it wasn't done I was placed back on a FHA loan when I could of saved more money by going conventional. Contacted the company and the manager agreed that Conversation could of been a better option but offered no way to remediate the companies lack of

[9] https://www.consumerfinance.gov/data-research/consumer-complaints/#download-the-data

> guiding me in the right direction. Not being presented with all the options has cost me about XXXX in the back end of the loan and about XXXX dollars more a month.[10]

While anecdotal evidence provides valuable insights into borrower-lender interactions, systematic data analysis provides more robust and informative results. In this section, I explores how lenders may affect the refinancing decisions of FHA borrowers. First, I present empirical evidence showing the heterogeneity in refinance outcomes by lenders. Lender fixed effects account for a significant portion of FHA refinance choices, after controlling for borrower characteristics. Next, I delve into potential incentives for lenders to favor originating FHA streamline refinances over GSE refinances. Finally, I use exogenous changes in FHA refinance loan profits to show that FHA refinance outcomes respond to these changes.

Empirical Evidence of Lender Fixed Effects

Do the refinancing outcomes of FHA borrowers correlate with the lenders they choose? In this section I will show empirical evidence to answer this question.

Lender Fixed Effects Explain Refinance Outcomes I first examine lender fixed effects in the regression explaining refinance choices:

$$y_{ijct} = \alpha + \beta X_i (+\gamma W_j) + \xi_{ct} + \varepsilon_{ijct} \tag{1.3}$$

y_{ijct} is the dummy variable indicating refinance to GSE loan conditional on the hedonic model predicted property value increase larger than 16.5% and FICO score greater than 620 at time of refinance. X_i are borrower controls including FICO score, the hedonic model predicted property value growth, loan amount, interest rate and time from purchase to refinance. ξ_{ct} is year and county fixed effects. W_j is lender fixed effects. I first run the regression without lender fixed effects, and then add the lender fixed effect. Adding lender fixed effects increases marginal R-squared from 38% to 48%. This result is robust to a series of alternative set of specifications (See Table A.2).

Heterogeneity across Lenders Then I show that lender type also correlates with the type of mortgage product (FHA or GSE) FHA borrowers refinance to. In Table 1.4, I run the similar specification as before:

$$y_{ijct} = \alpha + \beta L_j + \gamma X_i + \xi_{ct} + \varepsilon_{ijct} \tag{1.4}$$

y_{ijct} is the dummy variable indicating refinance to GSE loan conditional on the hedonic model predicted property value increase larger than 16.5% and FICO score greater than 620 at time of refinance. L_j are dummy variables indicating whether the lender originating the original loan that got prepaid is a bank, nonbank or credit union, as well as the lender originating the refinance loan is a bank, nonbank or credit union. X_i are borrower

[10] The exact date and values are redacted from the CFPB database for privacy concerns.

controls including FICO score at time of refinance, the hedonic model predicted property value growth, loan amount at refinance, refinance interest rate and time from purchase to refinance. ξ_{ct} is year and county fixed effects.

Table 1.5 presents the results, showing that after controlling for borrower characteristics, eligible FHA borrowers are less likely to refinance to a GSE loan when working with a nonbank lender than with a bank. Credit unions, despite their smaller market share, demonstrates higher likelihoods in borrowers switching to a GSE loan. This pattern persists regardless of whether the lender originated the purchase or refinance loan, indicating that lender are closely related to borrower refinancing decisions.

Nonbank Growth in FHA Market A notable trend about nonbank market share in FHA mortgages emerges from the analysis. Figure 1.9 plots the count of FHA mortgage origination from 2010 to 2018 from eMBS data. There is a persistent and fast growth in nonbank share of the FHA mortgage origination market. This trend implies that FHA borrowers increasingly refinance with nonbank lenders. Nonbanks are faced with less competition from other competing lenders who are subject to a different regulatory schedule. While the following sections will discuss how some policies contribute to the change in market structure, the current state of market structure itself appears to directly impact FHA refinance outcomes. Supporting this view, Buchak and Jørring (2021) show lenders in more concentrated markets charge higher fees. Figure 1.10 plots the probability of eligible FHA borrowers to refinance to a GSE mortgage on Herfindahl-Hirschman Index (HHI) at the county level. As market concentration increases, the probability of refinance to a GSE loan decreases. This result suggest lenders have market power to affect refinance choices.

Underwriting Fees and Processing Time

Why originating FHA streamline refinances may benefit lenders? FHA mortgages typically carry higher default risk and impose greater costs on borrowers. Home buyers who are eligible for a GSE mortgage generally prefer GSE mortgage over FHA mortgages to avoid overpaying on mortgage risk premiums. The same logic extends to refinance decisions. However, the payment on UFMIP and MIP are collected by the government agency, it is not obvious why lenders can benefit from originating more FHA mortgages. This section examines several factors that make FHA streamline refinancing attractive to lenders.

Higher Upfront Origination Fees FHA streamline refinancing generates higher upfront fees for lenders. Figure 1.11 summarizes the 2018-2020 HMDA data about origination costs, showing that an FHA refinance costs borrowers on average $3,000 (1.5% of average loan amount) more to originate than a GSE refinance. This cost to the borrowers translates into revenue for the lenders.

Why lenders can charge a higher upfront fee for FHA loan origination? While researchers do not have access to the exact decomposition of upfront fee at this time, some reports attributed the higher upfront fee to the corresponding conveyence cost in the event of mort-

gage default. According to a research by Urban Institute [11] , the combined first legal action penalty and property preservation loss can be as high as $9,539 (5.4% of loan amount) per nonperforming event.

> The FHA's conveyance process differs from that of the GSEs. Servicers of FHA mortgages have 30 days after foreclosure to repair the property and convey it to HUD with a clean title. The GSEs follow a direct conveyance model. They take possession of the property after the auction and hire vendors to perform repair before putting properties back on the market. Data show that the conveyance process significantly slows down property disposition and imposes heavy costs on the FHA, neighborhoods, communities, and servicers.

Notice that even though the average default risk for FHA mortgages (5%) is higher than the average default risk of GSE mortgages (1.5%), the FHA streamline refinanced mortgage pool exhibits a default rate that is much closer to GSE mortgages. This suggest that lenders' potential risk exposure to default event is much lower when they originate an FHA streamline refinance. This makes originating FHA streamline refinance mortgages profitable, since they can charge a high underwriting fee to borrowers whose risk are relatively low .

Faster Processing Time FHA streamline refinancing offers efficiency and cost advantages for lenders. Evidence suggests originating FHA streamline refinance is faster and thus incur less labor cost. According to Fuster et al. (2019), the average process time for refinance loan is 40-50 days. However, FHA streamline refinance FHA streamline refinance can take as little as 30 days.[12] This is partly because that property appraisal usually takes 1-2 weeks.[13]

Marketing materials provide additional evidence of lender preference for FHA streamline refinance. Grundl and Kim (2019) find that advertising increases the refinance probability who should refinance by approximately 5.6 percentage points. In their sample, nonbank lenders make up more than a half of the total direct mailings received. I found in these advertisements, the option of refinance to a GSE loan is missing and the fast and convenient feature of FHA streamline refinances is emphasised. For example, in the mail advertisement in Figure A.3, the nonbank lender emphasizes the "no appraisal" feature of FHA streamline refinance, and did not mention the potential higher cost of mortgage insurance premium. Another example advertisement from a fintech lender, the largest mortgage lender in the U.S. as of 2023, Rocket Mortgage (formerly Quicken Loans), explained the FHA streamline refinance options for FHA borrowers who are looking for a refinance in their online article, and also did not mention the option to refinance their FHA loan to a GSE loan in the entire article, as of April 2023. [14]

[11] Reforming the FHA's Foreclosure and Conveyance Processes by Karan Kaul, Laurie Goodman, Alanna McCargo, and Todd Hill, Feb 2018

[12] Mutual Mortgage. "Streamline Refinance FAQs." available at https://www.mutualmortgage.com/articles/refinancing/streamline-refinance-faqs/

[13] Pacres Mortgage. "Your Loan Timeline from Offer through Closing." available at https://pacresmortgage.com/knowledge-center/news-insights/your-loan-timeline-from-offer-through-closing

[14] https://www.rocketmortgage.com/learn/fha-streamline-refinance

Exogenous Shock in FHA Mortgage Revenue

Secondary Market Revenue Difference

According to Zhang (2022), the profit from upfront closing costs constitute approximately 20% of the total profit from mortgage origination with the remaining derived from secondary market sales. This is also consistent with the originate-to-distribute model discussed in Kim et al. (2018) and Kim et al. (2022). During the sample period of this paper, FHA mortgages are sold at a higher price in the secondary secularization market. Following Gete and Reher (2021), I compared the TBA MBS price for Ginnie Mae and GSE loans. As shown in Figure A.11, during the decade from 2010 to 2020, Ginnie Mae loans in TBA market are traded at a higher price than GSE (FNMA and FHLMC) loans during the sample period. FHA loans are fully guaranteed by the U.S. government. This full guarantee significantly reduces the risk for investors in the MBS market, making FHA-backed securities more attractive. Gete and Reher (2021) argued that lenders originate more FHA purchase mortgage by lowering the credit requirement. The Liquidity Coverage Ratio (LCR) regulation increased the attractiveness of securitized FHA loans by granting them favorable regulatory treatment. This caused a rise in the secondary market prices for these loans, reducing funding costs for nonbank lenders. In response, nonbanks loosened their lending standards and originated more FHA-insured mortgages. The expansion of FHA mortgage lending can reach the other side of the distribution– borrowers with good credit profile who are eligible for a GSE mortgage looking for a refinance.

Research Design

To test the causal relationship between lender incentives and refinance outcomes, I employ the same shock used in Gete and Reher (2021) to test the effect of LCR regulation change on FHA refinance mortgage origination. I perform a difference-in-difference analysis across lenders, quarters and loan types. The baseline regression equation is

$$y_{i,j,t} = \beta(Nonbank_j \times Premium_t) + \gamma X_{i,t} + \xi_c + \eta_t + \varepsilon_{i,j,t}$$

Where i, j, t index borrower, lender and time respectively. $y_{i,j,t}$ is a dummy variable indicating whether the qualified household refinances their FHA loan to a GSE loan. Qualified is defined as the property value growth from purchase to refinance exceeded 16.5% according to the hedonic model in the previous section and credit score is above 620 at the time of refinance. $Nonbank_j$ indicates if the lender is a nonbank. Similar to the literature, I use nonbanks as "treated lenders" and measure of relative price of GNMA MBS and GSE MBS as treatment. $X_{i,t}$ are borrower control variables including credit score, property value and loan amount. ξ_c is the county fixed effect.η_t is the year fixed effect.

The identifying assumption is that the LCR-induced increase in the GNMA premium does not coincide with unobserved shocks that affect nonbanks' propensity to prefer originating FHA streamline refinance over conventional loans to FHA borrowers looking for refinance, relative to banks' propensity. This asymmetry arises because nonbanks are more exposed to market-based funding and rely less on deposits, making them more sensitive to changes in the secondary market prices for mortgages. Banks, on the other hand, are more concerned about

the risk corresponded to originating FHA loans, for example the putback risk documented in Benson et al. (2023) and Mayer et al. (2023).

Results

The result are reported in Figure 1.12 and Table 1.6. After the implementation of new LCR rules, there is a decline in the probability of FHA-GSE refinancing with nonbanks, refinance outcome are 13% less likely to be a GSE mortgage. The results are statistically significant at the 1% level in all specifications. These results imply that higher GNMA price in the TBA market due to the introduction of the new LCR rules influenced the lending practice of nonbanks about FHA mortgage refinance.

Exogenous Shock in FHA Mortgage Cost

So far I have demonstrated how policy shocks affecting FHA mortgage revenue may influence FHA refinance outcomes. Next I examine the impacts of policy shocks affecting FHA mortgage cost. Specifically, increased putback risk from the False Claims Act (FCA) led banks to perceive higher costs in FHA mortgage origination, subsequently increased the probability of FHA-to-GSE refinance.

FCA and Bank Exit

Bank of America (BOA) exited the FHA mortgage market around 2012. This decision was largely in response to prosecutions by the Department of Justice (DOJ) under the False Claims Act (FCA). The use of the FCA in this context was unprecedented, enabled by the Fraud Enforcement and Recovery Act of 2009. The DOJ sued lenders for damages resulting from the government's losses due to fraudulent lending practices. According to Benson et al. (2023), Banks were disproportionately affected by these actions for two primary reasons: 1. They faced greater reputational risk. 2. Their substantial financial resources made it feasible for the government to put FHA mortgages back on their balance sheets. U.S. Bank paid the United States government $200 million to resolve allegations that it violated the False Claims Act by knowingly originating and underwriting mortgage loans insured by the Federal Housing Administration (FHA) that did not meet applicable requirements. [15] Jamie Dimon, Chase CEO, noted in a 2016 shareholder letter that "FCA settlements wiped out a decade of FHA profitability."[16] This shock increased the perceived risk associated with FHA lending, which out-weighted the benefits from originating FHA streamline refinance loans for banks, but not for nonbanks. Benson et al. (2023) find that in the FHA purchase mortgage market, bank market share significantly decreased. I extend the analysis to the FHA refinance market and test the effects of this policy shock in FHA mortgage cost on borrowers' mortgage refinance choice.

Research Design

I implement this identification strategy using a DID framework. Figure 1.13 shows the county level market share of BOA in FHA refinance mortgage dropped from 8% to 0% after

[15] https://www.justice.gov/opa/pr/us-bank-pay-200-million-resolve-alleged-fha-mortgage-lending-violations

[16] `https://reports.jpmorganchase.com/investor-relations/2016/ar-ceo-letters.htm`

2011. When BOA pulled back nationally from FHA origination, counties with larger BOA share are faced with higher change in the lenders' operating strategy, while other counties experienced insignificant changes in lenders' behavior. The regression equation is as follows:

$$y_{ict} = \sum_{\tau} \alpha_{\tau} S_c 1[\tau = t] + X_{ict}\gamma + \xi_c + \epsilon_{ict} \tag{1.5}$$

y_{ict} is the dummy variable indicating FHA borrowers refinance to GSE loan conditional on the hedonic model predicted property value increase larger than 16.5% and FICO score greater than 620 at time of refinance for borrower i in county c at time t. The treatment exposure S_c is measured in two ways. (1) The origination lender being BOA and (2) the county-level BOA market share pre-exit in 2010. X_{ict} are individual level control variables including credit score at time of refinance, the hedonic model predicted property value growth, loan amount at refinance, refinance interest rate and time from purchase to refinance. ξ_c is county fixed effect. In addition to the year-by-year regressions, I also include results pooling together periods before and after exit together, yielding a single DID estimate.

Results

Figure 1.15 and Figure 1.14 reports the year-by-year estimates of treatment effect, and Table 1.7 pools the treatment years together and reports the point estimate. After the exit of BOA, eligible FHA borrowers who obtained their FHA loan are 5% more likely to refinance to a GSE mortgage. Eligible borrowers residing in the counties where BOA used to have a high market share are more likely to refinance to a GSE loan. A 1% decrease in county BOA market share predicts about 2% increase in the probability of refinance to a GSE loan for eligible FHA borrowers. This effect is stronger over time 3 years after the exit event.

FHA borrowers typically first consult their original mortgage lender for refinancing options. After BOA exited the FHA market due to perceived higher cost associated with increased putback risk, BOA would guide borrowers to refinance to a GSE mortgage instead. Similar pattern happens in the region where BOA has a larger market share, because FHA borrowers who search for lenders to refinance their mortgage are more likely to consult with BOA, which would recommend a GSE refinance to them.

To summarize, financial intermediaries significantly influence FHA borrowers' refinancing choices. There is significant heterogeneity in refinance choices across lenders, with lender fixed effects accounting for a substantial portion of the variation in outcomes. Borrowers work with nonbank lenders are less likely to switch GSE loans. I discussed several factors that may incentivize lenders to favor FHA streamline refinances, including higher upfront fees, faster processing times, and higher secondary market prices for FHA securities. Analysis of exogenous shocks–both LCR regulation changes (affecting revenue) and FCA enforcement (affecting costs)–demonstrates that lenders respond to these policy changes, and significantly impact FHA borrowers' likelihood of refinancing to GSE loans.

1.7 Conclusion

Mortgage refinance is crucial for households to reduce their mortgage payment and for interest rate policy to pass through to the household sector. Frictions in mortgage refinance can both reduce the efficiency of interest rate policy and generate distributional mortgage payment inequality among households. This research introduces a novel mechanism understanding how FHA mortgage refinance choices are made, and quantify how actual FHA mortgage refinance choices deviates from model predicted optimal choices. From my estimation, 40% of FHA borrowers who refinanced their mortgage to a new FHA mortgage in the past decade were actually eligible for refinancing to a GSE mortgage. They would save about $110 per month and about $2,957 upfront on their mortgage payment by doing so, because they can remove the mortgage insurance premium that is no longer necessary for their actual equity level in the mortgage.

I find that both demand and supply side factors can explain the refinance frictions. On the demand side, information on property value appreciation helps FHA borrowers make better choice. On the supply side, lenders make more profit by originating FHA loans, and exogenous increase in lenders' revenue (cost) of originating FHA loans results in less (more) refinance to GSE mortgages.

This result has significant implications for policymakers seeking to improve the welfare of FHA borrowers. Based on my findings, policymakers can enhance the efficiency of mortgage refinancing and reduce the amount of mortgage money left on the table from both the credit demand and credit supply perspectives.

On the credit demand side, efforts should focus on reducing information frictions. Facilitating easier access to information about LTV changes and household balance sheet evolution over time can empower households to make better financial decisions. Additionally, information about how a household's balance sheet situation affects borrowing costs should be provided. Optimal refinancing choices involve not only responding to interest rate changes but also to property value fluctuations, as well as refinancing to the most suitable type of mortgage.

On the credit supply side, encouraging competition among lenders can mitigate the agency problem between borrowers and lenders, leading to more efficient mortgage refinancing choices. The results indicate that lenders have market power over borrowers, as refinancing outcomes change in response to lenders' profit margins. Increased competition, or reducing the search cost for borrowers to work with multiple lenders, can help address this imbalance.

Finally, it is important to note that policies designed to protect borrowers in one economic environment can inadvertently reduce borrower welfare in a different economic context. For example, the no-reassessment feature for FHA streamline refinancing protects borrowers who may be underwater during economic downturns. However, in a booming housing market, this feature may prevent borrowers from capitalizing on their property value growth and realizing potential savings on mortgage payments.

Given that FHA borrowers typically include minorities, individuals with low-to-moderate

incomes, and first-time home buyers, policies aimed at reducing frictions in their mortgage choices are likely to have a more significant impact on marginal housing market participants. Such policies could help reduce inequalities in housing costs and wealth accumulation across the United States.

Figures and Tables

Figures

Figure 1.1: Illustration of FHA Refinance Choice

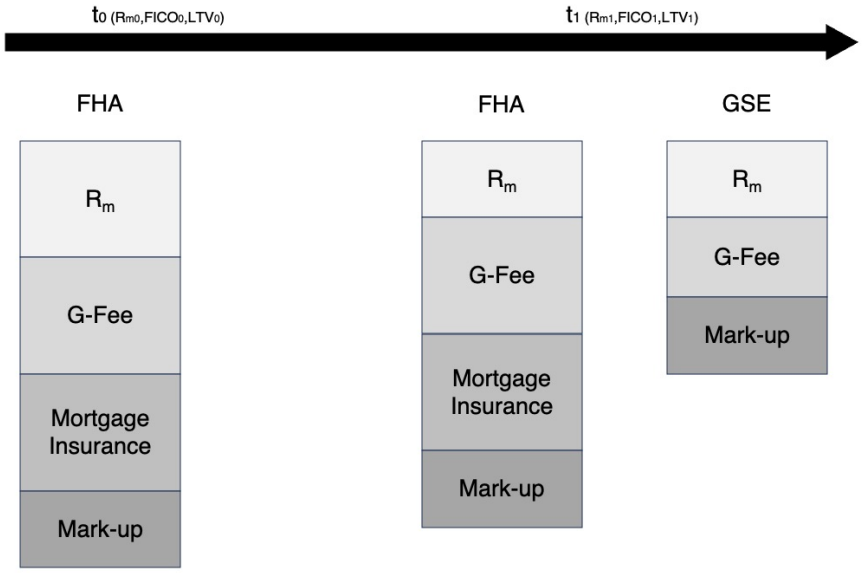
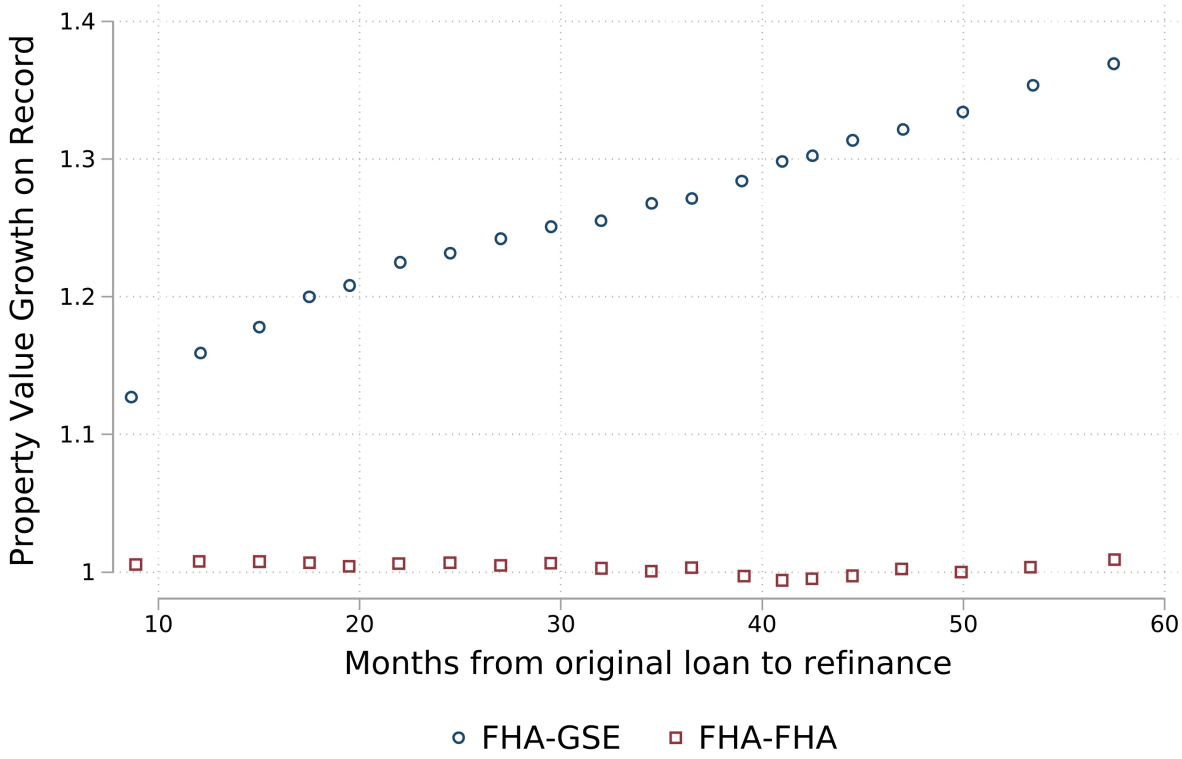
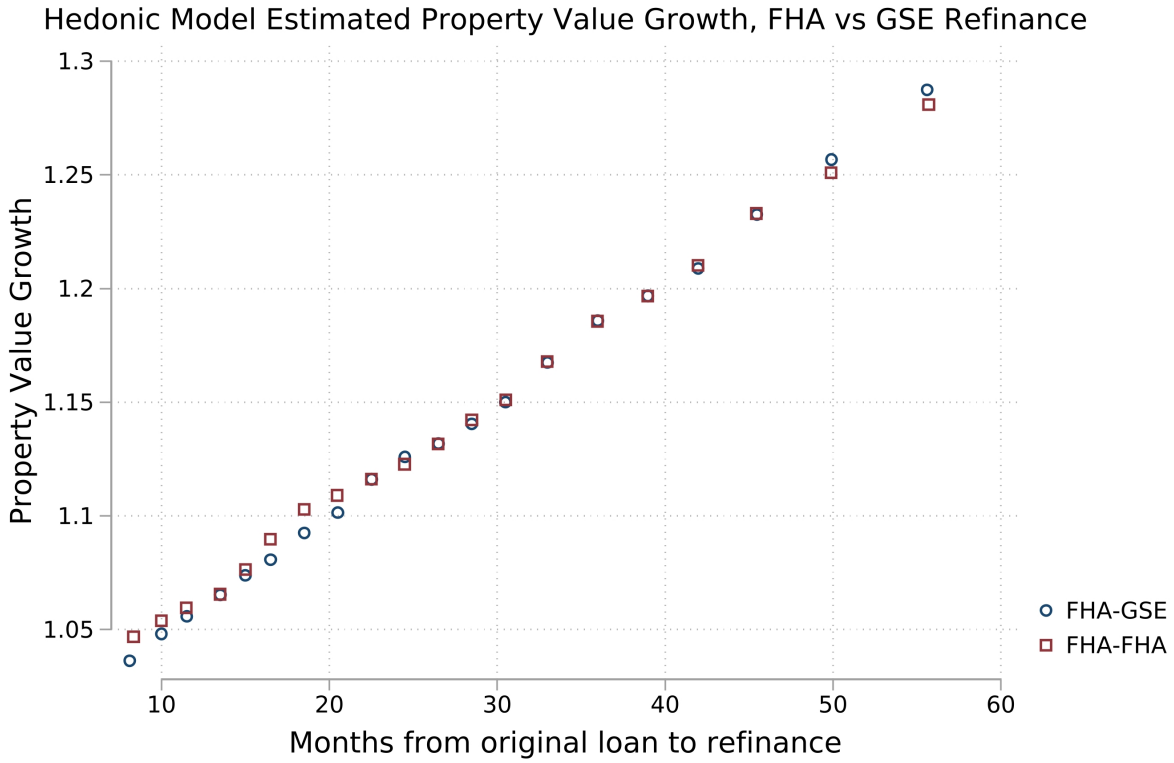


Figure 1.2: Property Value Growth on Refinance Application



Note: These figures plot the property value growth on mortgage refinance applications. The x-axis shows months from original loan to refinance. The y-axis shows the property value on refinance profile, divided by the property value at purchase. The blue circle represents the group where the FHA purchase loan was refinanced to a GSE loan; the red square represents the group where the FHA purchase loan was refinanced to another FHA loan.
Source: ATTOM, McDash.

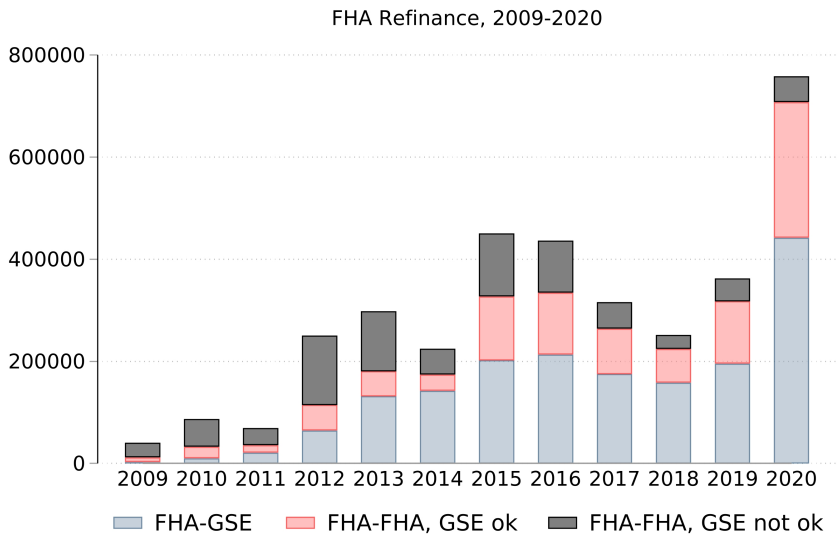
Figure 1.3: Property Value Growth Estimated by Hedonic Pricing Model



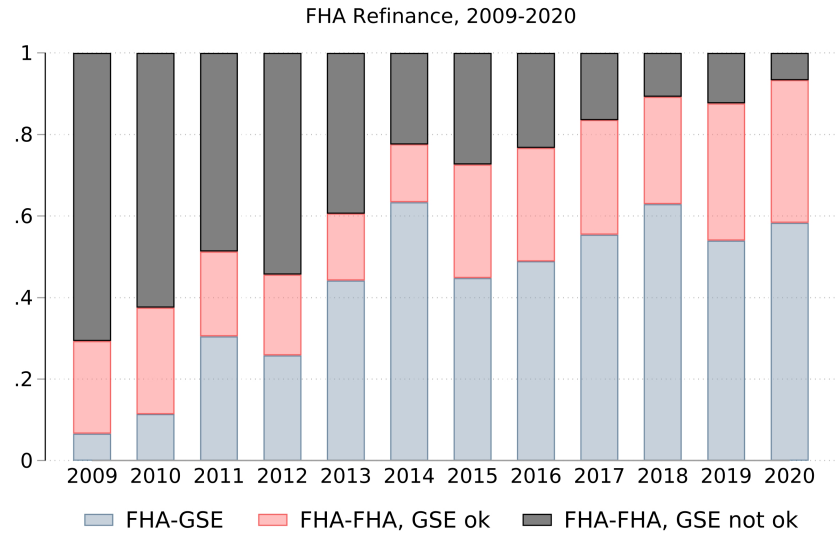
Note: Note: These figures plot the hedonic-model predicted property value growth. The x-axis shows months from original loan to refinance. The y-axis shows the property value estimated by hedonic model at refinance time divided by the property value at purchase. The blue circle represents the group where the FHA purchase loan was refinanced to a GSE loan; the red square represents the group where the FHA purchase loan was refinanced to another FHA loan.
Source: HMDA, ATTOM, McDash, author's own calculations.

Figure 1.4: Identified Suboptimal Refinance Choices

Panel A: Count of Refinance Choices by Year



Panel B: Share of Refinance Choices by Year

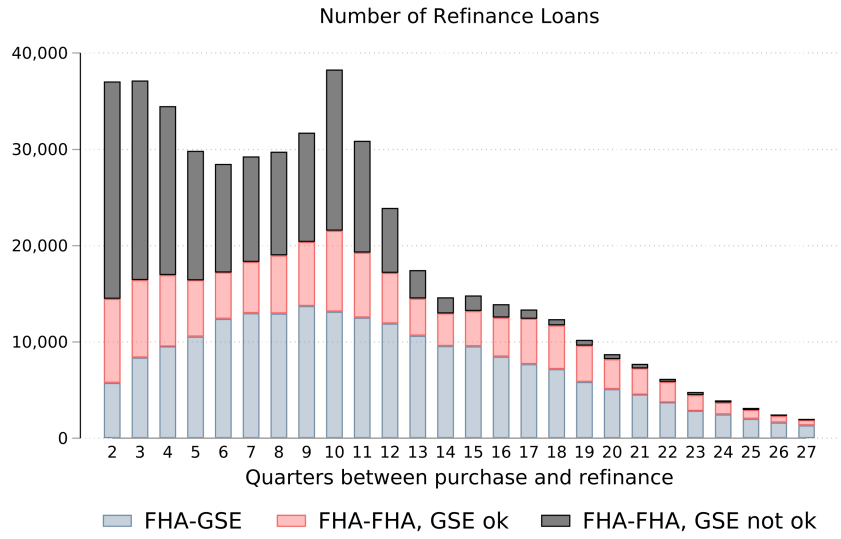


Note: These figures plot the distribution of FHA refinance choices across years. The blue bar at the bottom represents FHA loans refinanced to a GSE loan. The red bar in the middle represents the FHA loans refinanced to an FHA loan, but have a FICO score greater than 620 at the time of refinance and experienced 16.5% property value growth according to the hedonic model described in Section 1.3. The grey bar on the top represents FHA loans refinanced to another FHA loan but do not satisfy the above standards at the time of refinance. Panels A plots the count and Panel B plots the share.

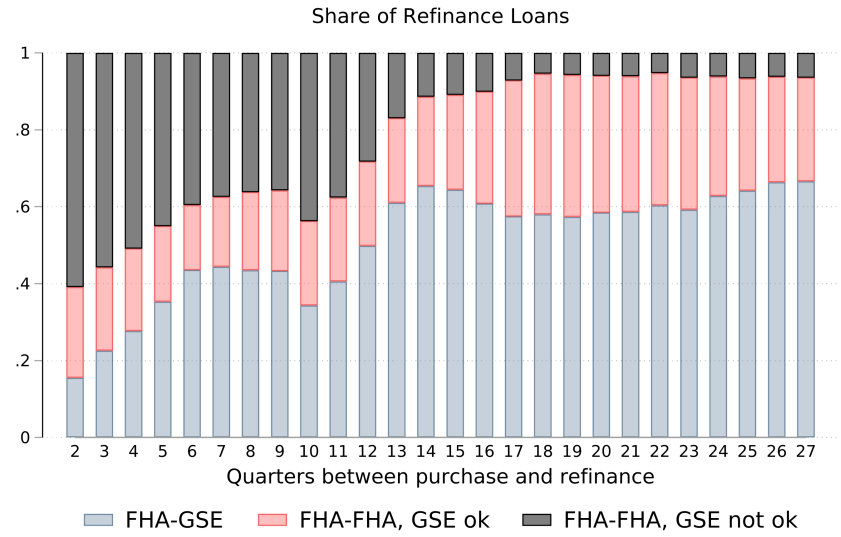
Source: HMDA, ATTOM, McDash, author's own calculations.

Figure 1.5: Identified Suboptimal Refinance Choices

Panel A: Count of Refinance Choices by Quarters from Purchase to Refinance



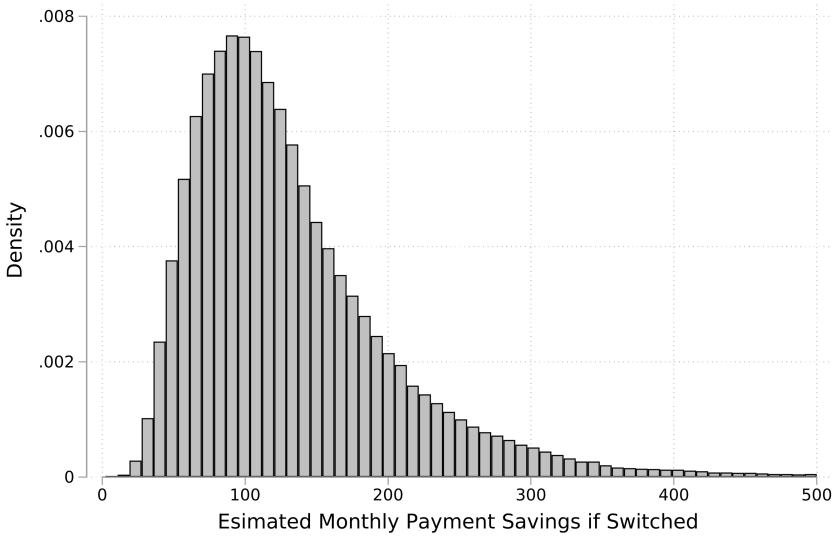
Panel B: Share of Refinance Choices by by Quarters from Purchase to Refinance



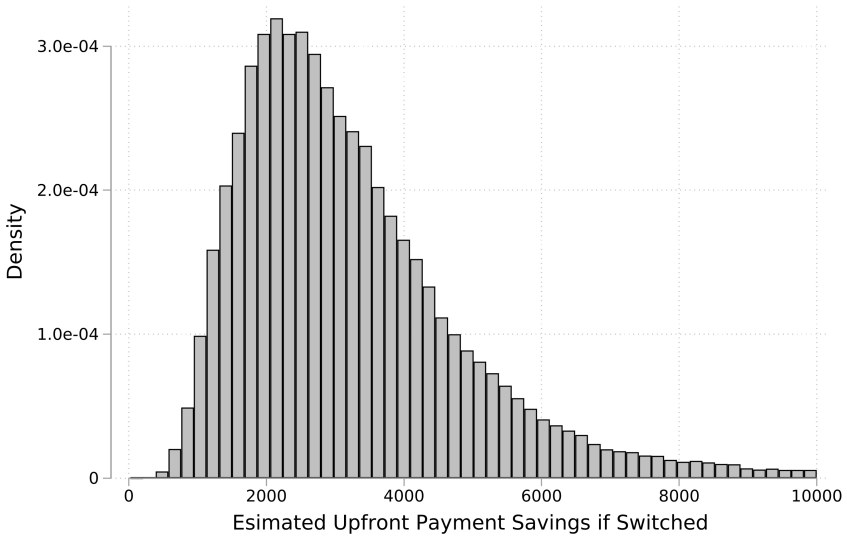
Note: These figures plot the distribution of FHA refinance choices across years. The blue bar represents FHA loans refinanced to a GSE loan. The red bar represents the FHA loans refinanced to another FHA loan, but have a FICO score greater than 620 at the time of refinance and experienced 16.5% property value growth according to the hedonic model described in Section 1.3. The grey bar represents FHA loans refinanced to another FHA loan but do not satisfy the above standards at the time of refinance. Panels A plots the count and Panel B plots the share.
Source: HMDA, ATTOM, McDash, author's own calculations.

Figure 1.6: Distributions of Estimated Mortgage Savings

Panel A: Distribution of Estimated Monthly Mortgage Payment Savings

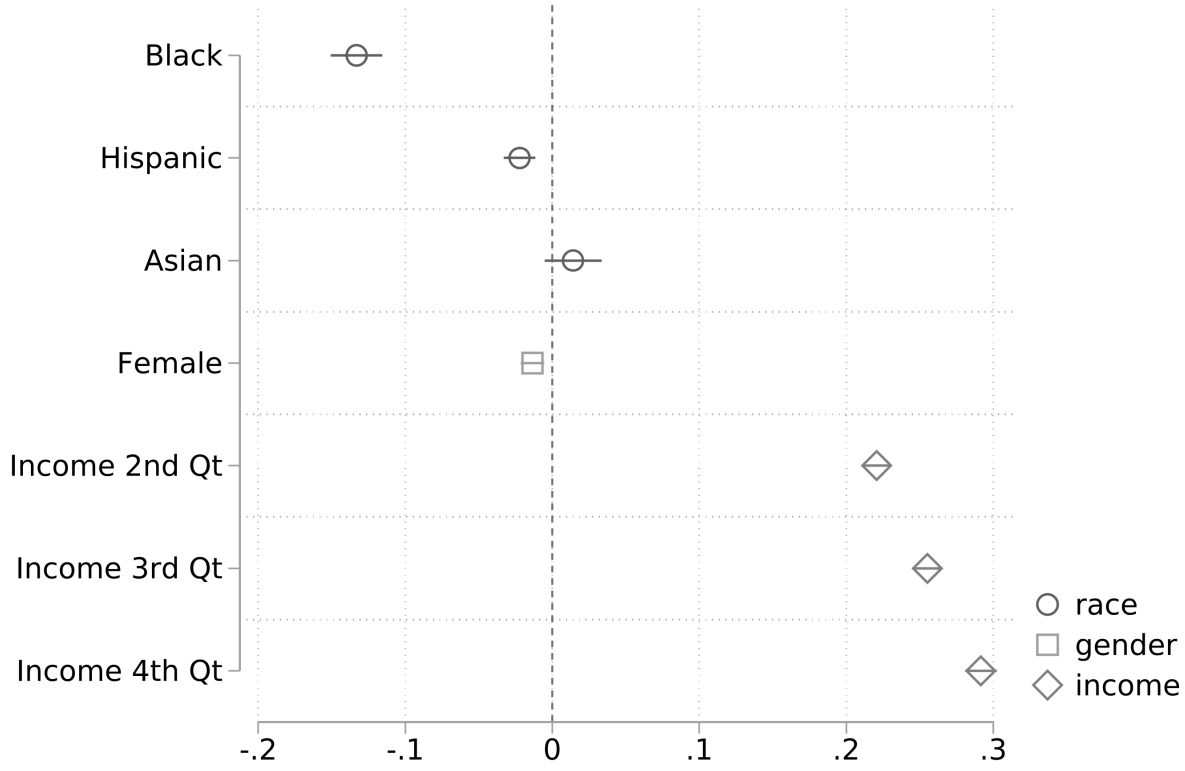


Panel B: Distribution of Estimated Upfront Mortgage Payment Savings



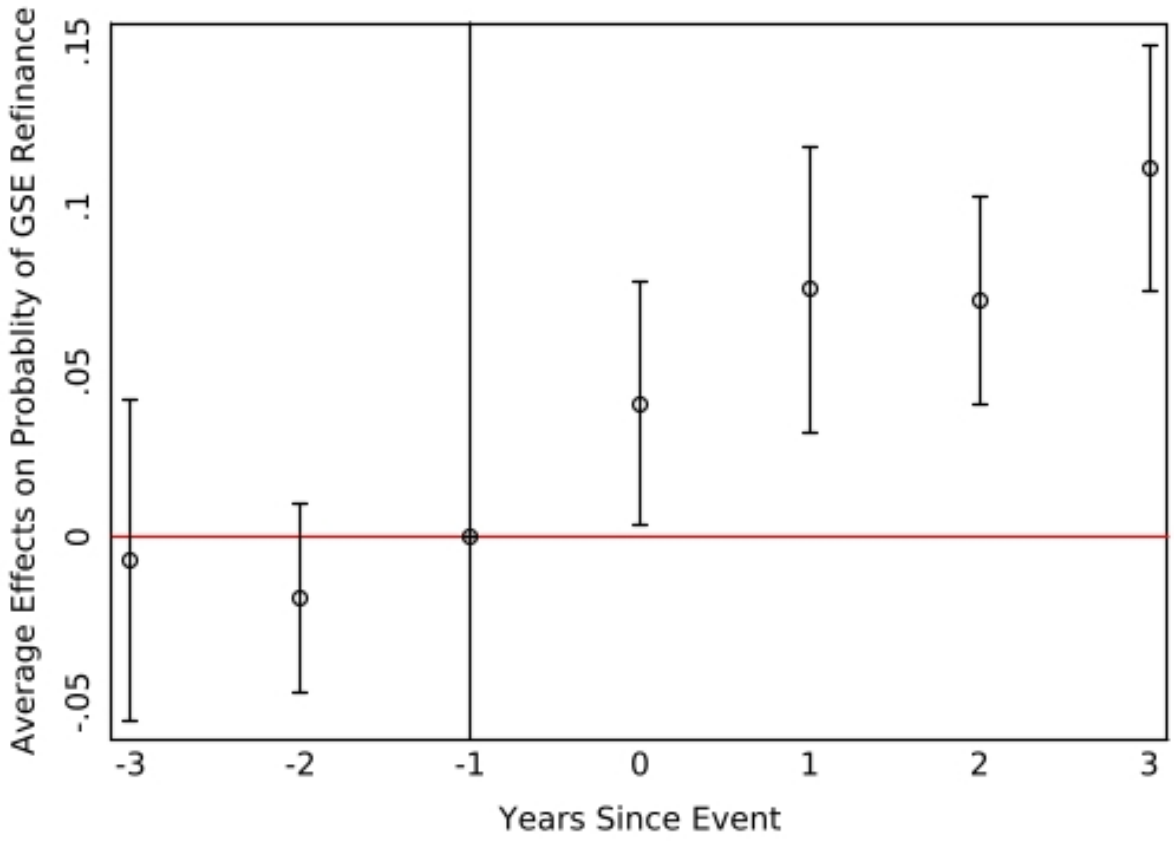
Note: This figure plots the histogram distribution of estimated savings in dollar amount if eligible FHA borrowers who conducted an FHA streamline refinance switched to a GSE refinance. Panel A plots monthly savings and panel B plots upfront savings. The savings on monthly payment is the monthly MIP at the time of refinance adjusted by average rate difference for the corresponding FICO score and LTV bin in the LLPA table. The savings on upfront payment is the UFMIP at the time of refinance adjusted by UPMIP reimbursement.
Source: HMDA, ATTOM, McDash, author's own calculations.

Figure 1.7: Heterogeneity in Share of FHA-GSE Refinance



Note: This figure plots the heterogeneity in share of eligible FHA borrowers refinance to a GSE mortgage. The dependent variable is a dummy variable indicating refinance to a GSE mortgage. The regression controls year and county fixed effect, borrower FICO score, refinance loan amount and interest rate, property value and estimated property value growth. The bars plot 95% confidence intervals for each point estimate. Robust standard errors are reported.
Source: HMDA, ATTOM, McDash, author's own calculations.

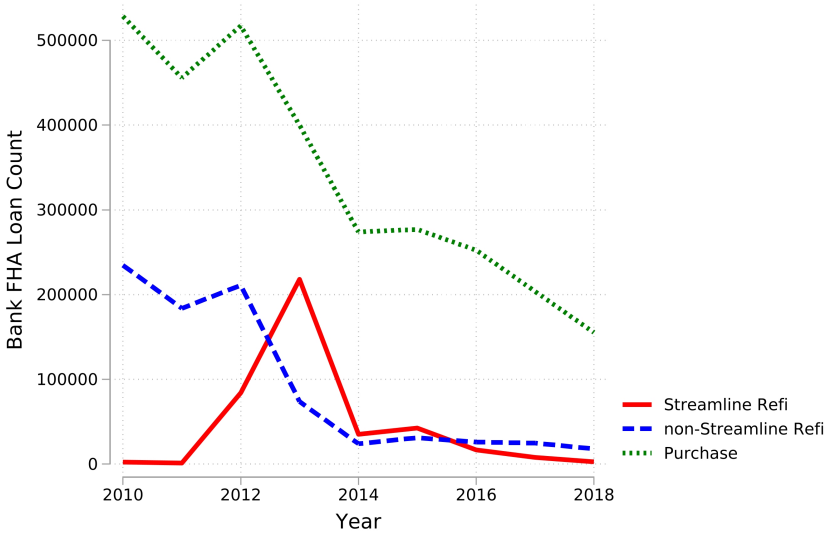
Figure 1.8: Effect of New Tax Bill on Refinance Choice



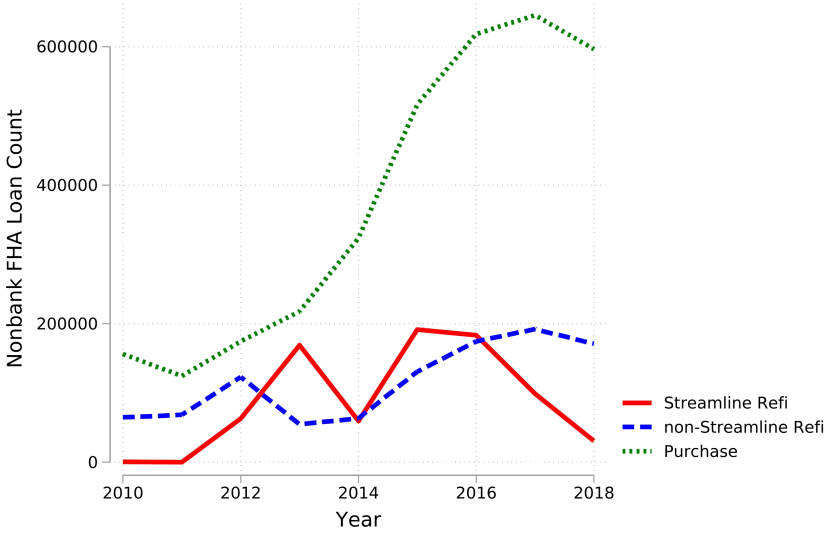
Note: This figure plots the effect of information treatment on refinance choice by equation 1.2. The y-axis measures the effects on probability to refinance to a GSE loan given eligible. The x-axis is the relative years to the event year, with -1 as the baseline year. The regression includes county fixed effects and lender FICO score, property value as controls. The line plots the 95% confidence intervals for each point estimate. Robust standard errors are clustered at county level.
Source: HMDA, ATTOM, McDash, author's own calculations.

Figure 1.9: FHA Mortgage Origination by Lender, 2010-2018

Panel A: Count of FHA Mortgages Originated by Banks

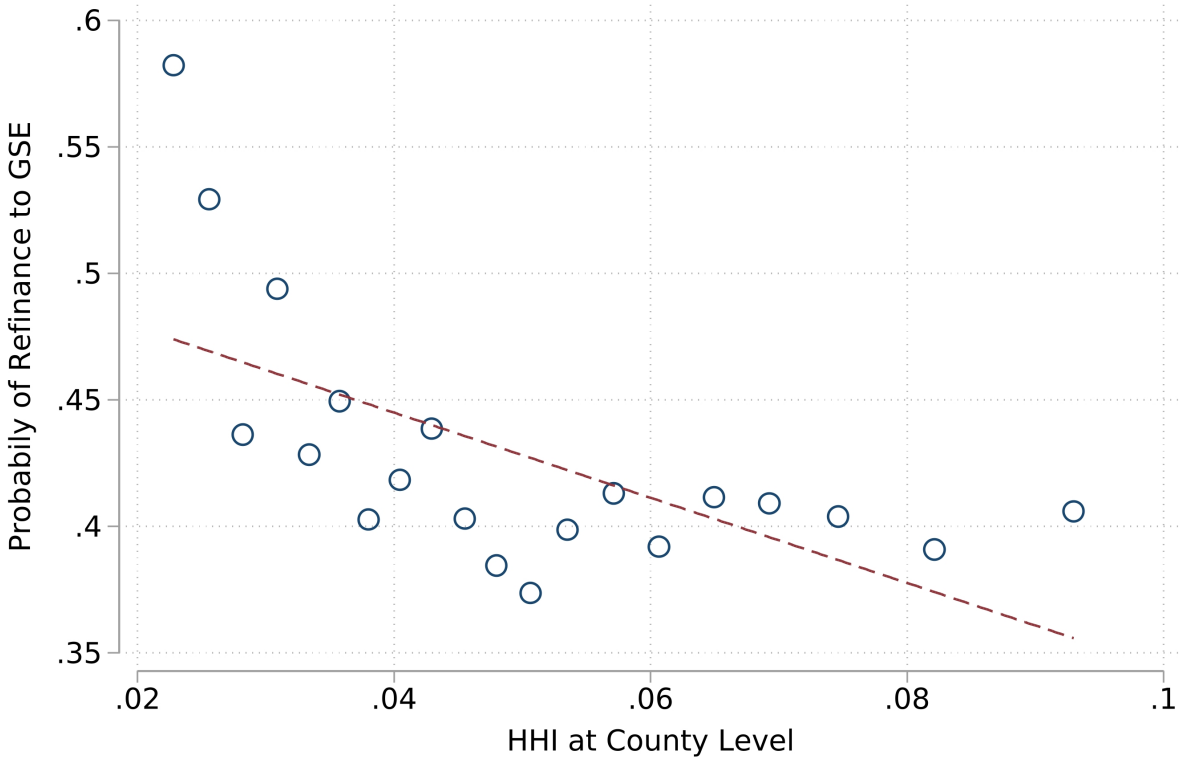


Panel B: Count of FHA Mortgages Originated by Nonbanks



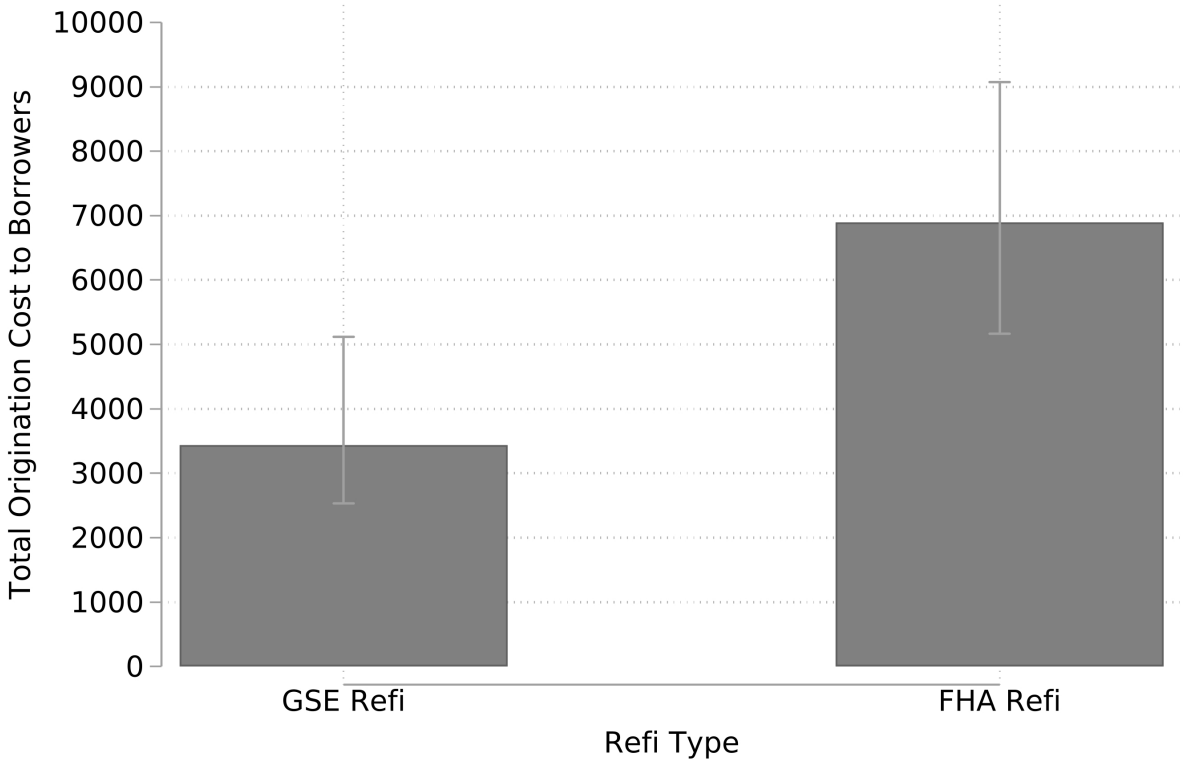
Note: This figure plots the count of FHA mortgage origination by year from 2010 to 2018. The red solid line represents FHA streamline Refinance and the blue dash line represents other FHA refinance. The green line represents FHA purchase mortgages. Panel A plots bank origination and panel B plots nonbank origination.
Source: eMBS

Figure 1.10: Refinance Choices and Market Competition



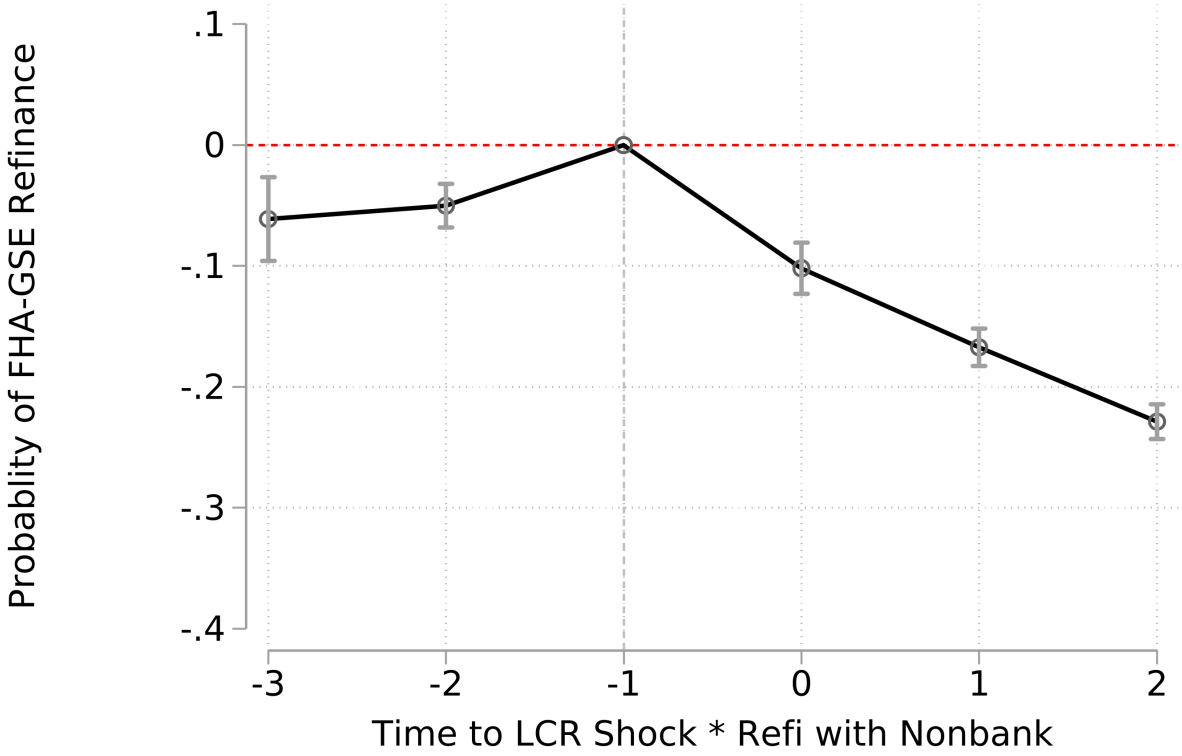
Note: This figure plots the correlation between market concentration and FHA refinance outcome. The x-axis is Herfindahl-Hirschman Index (HHI) at county level, calculated using HMDA data. The y-axis is the probability of eligible FHA borrowers to refinance to a GSE mortgage.
Source: HMDA, ATTOM, McDash, author's own calculations.

Figure 1.11: Upfront Fees from HMDA 2019



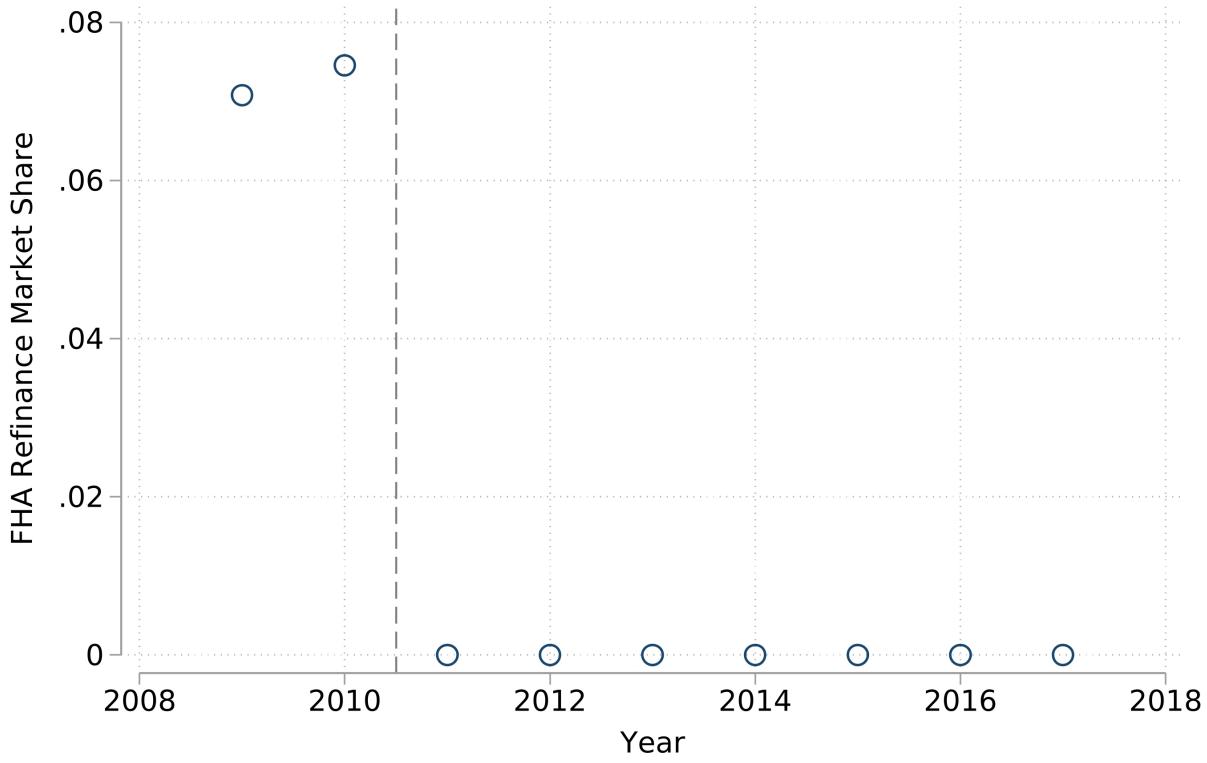
Note: This figure plots the upfront cost charged by lenders reported in HMDA 2019 data. The bar graph plots the median total cost and the capped lines shows the inter-quartile range. Th number of observations are 307,232 for FHA refinance and 1,652,120 for GSE refinance.
Source: HMDA.

Figure 1.12: Effect of LCR Schock on Refinance Outcome



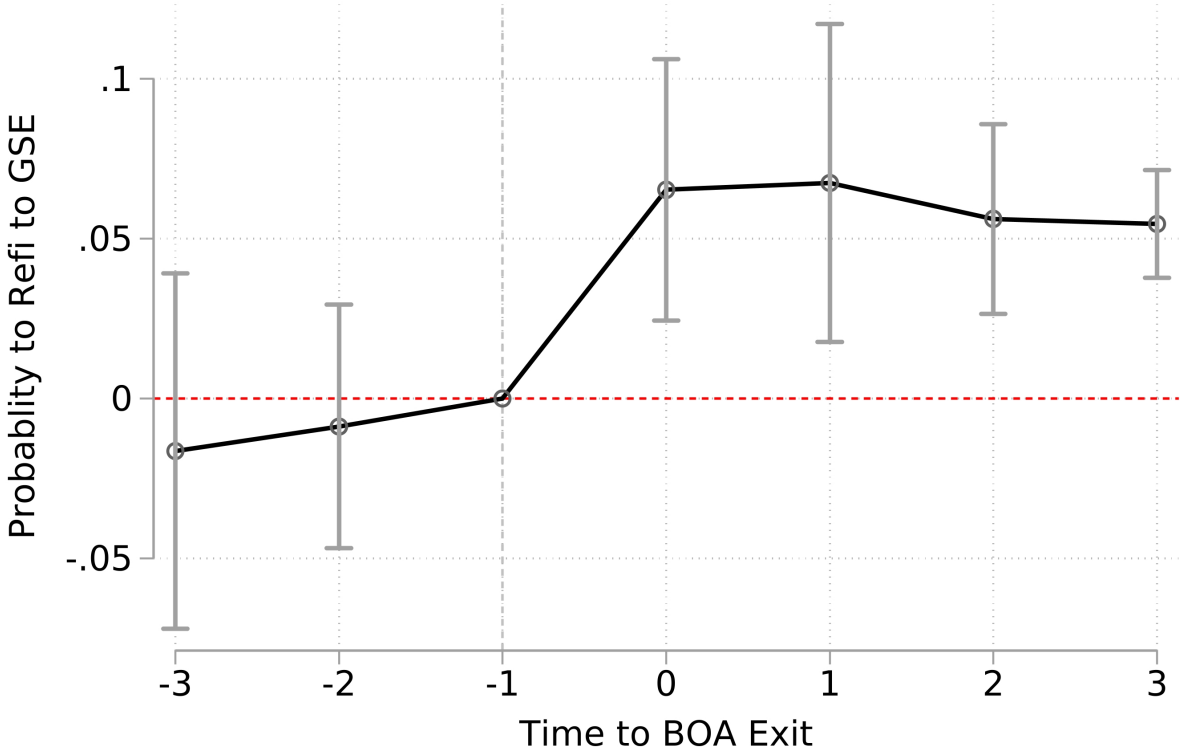
Note: This figure plots the effect of liquidity coverage ratio (LCR) shock on refinance choice. The regression is defined in equation 1.6. The y-axis measures the effects on probability to refinance to a GSE loan given eligible. The x-axis is the relative years to the event year, with -1 as the baseline year. The regression includes county fixed effects and borrower FICO score, property value as controls. The line plots the 95% confidence intervals for each point estimates. Robust standard errors are clustered at county level.
Source: ATTOM, McDash, TRACE author's own calculations.

Figure 1.13: Bank of America Exit Event



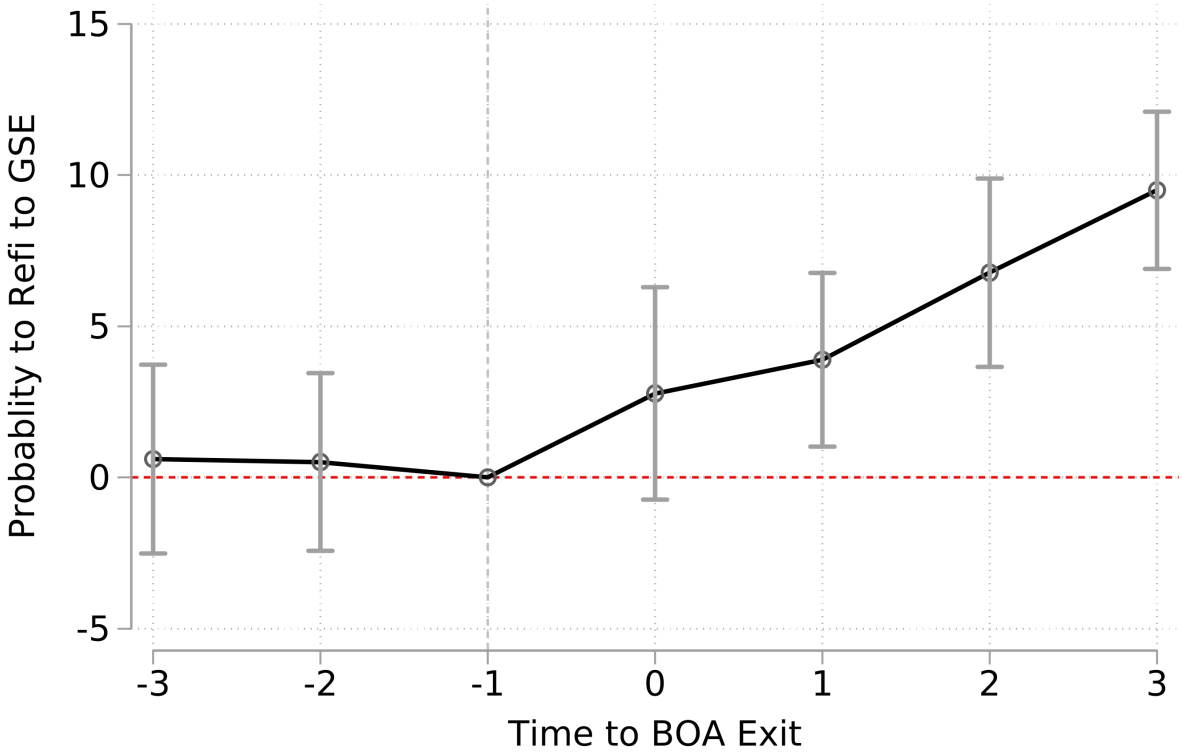
Note: This figure plots the average county level market share of Bank of America for FHA refinance origination. As a response to the law suits with DOJ on False Claim Act, Bank of America decided to stop originating FHA loans, both in the FHA purchase loan market and FHA refinance market.
Source: HMDA, author's own calculations.

Figure 1.14: DID Estimation on BOA Exit Event



Note: This figure plots the treatment effects of BOA exiting FHA market by event year, estimated by Equation 1.5. The y-axis measures the effects on probability to refinance to a GSE loan given eligible. The x-axis is the relative years to the year of BOA exiting FHA market, with -1 as the baseline year. The regression includes county fixed effects and lender FICO score, property value as controls. The line plots the 95% confidence intervals for each point estimates. Robust standard errors are clustered at county level. *Source:* HMDA, ATTOM, McDash, author's own calculations.

Figure 1.15: DID Estimation on BOA Exit Event



Note: This figure plots the treatment effects of a 100% decline in BOA market share on refinance choice by event year, estimated by Equation 1.5. The y-axis measures the effects on probability to refinance to a GSE loan given eligible. The x-axis is the relative years to the year of BOA exiting FHA market, with -1 as the baseline year. The regression includes county fixed effects and lender FICO score, property value as controls. The line plots the 95% confidence intervals for each point estimates. Robust standard errors are clustered at county level.

Source: HMDA, ATTOM, McDash, author's own calculations.

Tables

Table 1.1: Summary Statistics

Panel A: FHA-GSE Observations = 216,080

Variables	Mean	SD	p25	Median	p75
Montly Pmt. (Prepaid Loan)	1210.8	554.9	775.7	1067.6	1476.82
Montly Pmt. (Refi. Loan)	1182.1	680.7	755.4	1044.3	1454.7
Int. Rate (Prepaid Loan)	0.0448	0.00677	0.0388	0.0450	0.0500
Int. Rate (Refi. Loan)	0.0431	0.00534	0.0388	0.0425	0.0463
LTV at Origination (Prepaid Loan)	0.920	0.0978	0.899	0.962	0.981
LTV at Origination (Refi. Loan)	0.759	0.128	0.693	0.776	0.821
FICO (Prepaid Loan)	709.6	50.89	670	706	751
FICO (Refi. Loan)	729.7	50.08	695	733	770
Prop. Value (Prepaid Loan)	250,912	135,126	155,000	218,000	310,000
Prop. Value (Refi. Loan)	317,524	166,172	200,000	276,000	391,000
Time to Refinance	47.16	29.25	28	44	65

Panel B: FHA-FHA Observations = 306,481

Variables	Mean	SD	p25	Median	p75
Montly Pmt. (Prepaid Loan)	1245.2	622.7	817.2	1117.3	1518.8
Montly Pmt. (Refi. Loan)	1061.5	617.4	787.9	1066.9	1442.9
Int. Rate (Prepaid Loan)	0.0496	0.00634	0.0450	0.0500	0.0550
Int. Rate (Refi. Loan)	0.0404	0.00533	0.0375	0.0388	0.0437
LTV at Origination (Prepaid Loan)	0.932	0.0887	0.916	0.967	0.982
LTV at Origination (Refi. Loan)	0.903	0.101	0.865	0.935	0.970
FICO (Prepaid Loan)	697.9	52.99	657	692	739
FICO (Refi. Loan)	706.6	54.32	666	702	750
Prop. Value (Prepaid Loan)	238,882	118,074	157,000	214,000	290,000
Prop. Value (Refi. Loan)	248,403	125,214	162,000	220,000	300,000
Time to Refinance	35.03	26.99	16	32	47

Note: This table summarizes the characteristics of the merged population of borrowers who purchased their property with an FHA mortgage after 2009 and refinanced their FHA mortgage before the end of 2020. Panel A summarized the FHA borrowers who refinanced to a GSE mortgage and Panel B summarized the FHA borrowers who refinanced to a new FHA mortgage.
Source: HMDA, ATTOM, McDash, author's own calculations.

Table 1.2: Summary of Estimated Overpayment on Mortgage Insurance Premium

Panel A: Sensitivity of Identified Suboptimal Choices

FICO	620	620	680	680
ΔLTV	16.5%	20%	16.5%	20%
Share of Suboptimal Choices	40.99%	25.96%	28.3%	24.15%

Panel B: Quantify the Savings on Mortgage Payment

	Mean	SD	P25	Median	P75
Interest Rate	4.06%	0.53%	3.75%	3.99%	4.38%
Loan Amount	195,106	103,023	133,000	176,000	235,000
FHA MIP (bp)	95.95	21.50	85	85	115
Actual Payment ($)	1048.00	569.32	714.43	948.39	1258.74
Counterfactual Payment ($)	938.02	515.81	634.96	845.07	1127.18
Payment Savings ($)	109.98	59.98	72.19	99.55	134.49
Income (in $1,000)	78.74	74.45	48	67	93
Savings as Income Percentage	1.68%	0.97%	1.80%	1.78%	1.74%
Savings on UFMIP	2957.21	1713.28	1914.5	2632	3628

Note: This table summarizes the Estimated Overpayment on the Mortgage Insurance Premium. Panel A summarizes identified suboptimal choices under different credit score at the time of refinance and LTV change cutoff. Panel B shows the summary statistics of suboptimal FHA-FHA refinance loans and how much they could have saved by refinance to a GSE loan instead.
Source: HMDA, ATTOM, McDash, author's own calculations.

Table 1.3: Information Treatment Effects on Refinance Choice

	(1)	(2)	(3)
VARIABLES	Full Sample	High FICO	High Property Value
After	0.122***	0.159***	0.0901***
	(0.0194)	(0.0206)	(0.0194)
Constant	0.382***	0.459***	0.408***
	(0.0133)	(0.0138)	(0.0133)
Observations	11,455	6,694	7,487
R-squared	0.127	0.091	0.131
FICO Score Bin	Y	Y	Y
County FE	Y	Y	Y

County clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the estimates of the information treatment effects on refinance choice by equation 1.2. The dependent variable is a dummy variable indicating refinance to a GSE loan given model predicted property value growth greater than 16.5% and FICO score at the time of refinance greater than 620. Column (1) regress the full sample with county and lender FICO score fixed effects. Column (2) restrict the sample to borrowers with FICO score greater than 700 and Column (3) restrict the sample to borrowers with above median property value to rule out the potential income effect due to raised property tax.

Table 1.4: Regression Results on Refinance Choice and Refinance Lender

	(1)	(2)	(3)	(4)
VARIABLES	Baseline	Zillow Index	High FICO	High FICO Zillow
Nonbank	-0.136***	-0.142***	-0.144***	-0.133***
	(0.00236)	(0.00211)	(0.00275)	(0.00239)
Credit Union	0.211***	0.219***	0.143***	0.188***
	(0.00471)	(0.00537)	(0.00544)	(0.00562)
Loan Amount	2.38e-07***	7.87e-08***	1.84e-07***	1.40e-07***
	(1.43e-08)	(1.27e-08)	(1.59e-08)	(1.39e-08)
Time to Refi	0.000944***	0.00415***	0.00115***	0.00466***
	(8.72e-05)	(5.69e-05)	(0.000112)	(6.79e-05)
Prop Val Growth (Model)	0.166***		0.174***	
	(0.0158)		(0.0193)	
Prop Val Growth (Zillow)		0.192***		0.185***
		(0.00604)		(0.00697)
Constant	0.427***	0.162***	0.484***	0.186***
	(0.0184)	(0.00754)	(0.0219)	(0.00856)
Observations	142,975	176,119	89,265	131,632
R-squared	0.156	0.335	0.184	0.332
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows OLS estimates of a linear probability model on factors correlated with FHA borrowers refinance choice. The dependent variable is a dummy variable indicating refinance to a GSE loan given model predicted property value growth greater than 16.5% and FICO score at the time of refinance greater than 620. Column (1) and (2) use the full sample of FHA borrowers, and column (3) and (4) only look at borrowers with FICO score greater than 680. Column (1) and (3) use the hedonic model and column (2) and (4) use Zillow Home Value Index to measure property value growth.

Table 1.5: Regression Results on Refinance Choice and Lender

VARIABLES	(1) Original Lender	(2) Refi Lender	(3) Both Lenders
Purchase w/ Nonbank	-0.0334***		-0.0125***
	(0.00248)		(0.00247)
Purchase w/ Credit Union	0.0579***		0.0105
	(0.0202)		(0.0197)
Refi w/ Nonbank		-0.136***	-0.134***
		(0.00236)	(0.00240)
Refi w/ Credit Union		0.211***	0.212***
		(0.00471)	(0.00472)
Loan Amount	2.47e-07***	2.38e-07***	2.39e-07***
	(1.45e-08)	(1.43e-08)	(1.43e-08)
Prop Val Growth	0.219***	0.166***	0.167***
	(0.0162)	(0.0158)	(0.0158)
Time to Refi	0.000991***	0.000944***	0.000943***
	(9.00e-05)	(8.72e-05)	(8.72e-05)
Constant	0.308***	0.427***	0.433***
	(0.0186)	(0.0184)	(0.0184)
Observations	142,975	142,975	142,975
R-squared	0.128	0.156	0.156
Year FE	Y	Y	Y
County FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows OLS estimates of a linear probability model on factors correlated with FHA borrowers refinance choice. The dependent variable is a dummy variable indicating refinance to a GSE loan given model predicted property value growth greater than 16.5% and FICO score at the time of refinance greater than 620. Column (1) only look at the lender of purchase loan, column (2) only look at the lender of refinance loan, column (3) include both purchase loan and refinance loan.

Table 1.6: LCR Shock Effect on Refinance Choice

VARIABLES	(1) FHA-GSE	(2) Spread
$Nonbank \times t \geq 2013$	-0.130***	
	(0.0109)	
$Nonbank \times Premium$		-0.0357***
		(0.0127)
Nonbank	-0.0685***	-0.168***
	(0.0103)	(0.00668)
Constant	0.208***	0.146***
	(0.0375)	(0.0378)
Observations	63,543	62,731
R-squared	0.263	0.262
MSA-Year FE	Y	Y
Borrower Controls	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the estimates of the treatment effects of annoucement of Liquidity Coverage Ratio Rules on FHA refinance choice by equation 1.6. The dependent variable is a dummy variable indicating refinance to a GSE loan given model predicted property value growth greater than 16.5% and FICO score at the time of refinance greater than 620. Column (1) measures LCR by an indicator of $t > 2013$, the year before LCR regulation was announced.. Column (2) measures LCR shock by the difference in price between GNMA MBS and GSE (FNMA and FHLMC) MBS in the TBA market.

Table 1.7: BOA Exit Effect on Refinance Choice

VARIABLES	(1) BOA Exit	(2) BOA Exit
After * Pre-exit BOA Share	2.148***	1.878**
	(0.773)	(0.751)
Nonbank Lender		-0.169***
		(0.00209)
FICO Score	0.00189***	0.00183***
	(2.07e-05)	(1.84e-05)
Interest Rate	-11.13***	-10.45***
	(0.211)	(0.201)
Loan Amount	-5.73e-08***	-4.99e-08***
	(1.24e-08)	(1.21e-08)
Time to Refinance	0.00128***	0.000934***
	(5.43e-05)	(5.09e-05)
Observations	168,578	175,095
R-squared	0.307	0.330
Year FE	Y	Y
County FE	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the estimates of the treatment effects of a 100% decline in BOA market share on refinance choice by equation 1.5. The dependent variable is a dummy variable indicating refinance to a GSE loan given model predicted property value growth greater than 16.5% and FICO score at the time of refinance greater than 620. Column (1) is the baseline regression with controls of borrower characteristics. Column (2) add the control variable of refinance with a nonbank lender.

Chapter 2

Mortgage Refinance Under Present Bias: Evidence From The Use Of Lender Credits

2.1 Introduction

Mortgage decisions are among the most significant financial decisions for households. Yet, costly mistakes in refinancing choices prevail in the mortgage market (Agarwal et al., 2016; Keys et al., 2016; Agarwal et al., 2017). In the past decade since the Great Financial Crisis, U.S. policymakers have implemented multiple rounds of policies that lower mortgage rates, enabling households to reduce their debt burdens by refinancing existing mortgages at lower rates—a mechanism well-known as the mortgage refinance channel (Di Maggio et al., 2020; Berger et al., 2021). However, a significant share of households remain reluctant or even fail to take advantage of refinancing opportunities, due to substantial mental, physical or pecuniary costs involved in refinancing. Conversely, a sizable proportion of households refinance too early, forgoing the chance to achieve greater savings.

Apart from timing, another important aspect of refinancing decision is the choice of refinance product. Given that upfront costs may hold households back from refinancing, lenders increasingly provide financial products that feature "no-closing-cost refinancing". However, these product names can be misleading. What the lenders are actually providing is a refinancing product that incorporates the closing costs (appraisal fees, loan origination fees, etc.) in the principal amount of the new loan. These products use lender credits—or "negative points"—whose mechanism has been discussed in the literature (Stanton and Wallace, 1998). But the actual usage and its welfare implications remain an open question.

How can we reconcile the opposing timing errors in refinancing, either too early or too late? How are the choices of *when* to refinance and *what* product to use being jointly made? In particular, how does the use of lender credits imply for refinancing decisions and household welfare? In this paper, we investigate and emphasize the role of *present bias*—the tendency

to overrate instantaneous gratification in intertemporal choices—in household's refinancing choices.[1] We first propose a theoretical model in which households can select one from two refinancing products: (i) the regular refinancing, or (ii) the reduced-cost refinancing, which (partially) reduces the upfront closing costs paid out of pocket but adds it to the loan amount instead. Households will decide whether to pay refinancing costs upfront or defer them through higher interest payments, based on their intertemporal preferences. Given their chosen refinancing product, households then decide the timing of refinancing when the interest rate drops below a threshold. The key tension in timing is between the benefit of locking in current interest rate savings and the cost of forgoing the option value of waiting. Crucially, we compare households with present bias in their refinancing decisions to classic full rational models. Since both product selection and the timing of refinancing involve intertemporal trade-offs, present bias plays a central role in shaping refinancing patterns.

Our main theoretical result characterizes households' refinancing product choices and the corresponding thresholds on interest rate drops that trigger refinancing under different levels of present bias. We show that, under proper conditions, households' refinancing choices can be classified into the following three categories based on the extent of their present bias:

(i) Households with sufficiently high present bias tend to forgo the opportunity of refinancing altogether;

(ii) Households with intermediate levels of present bias tend to adopt reduced-cost refinancing;

(iii) Households with sufficiently low levels of present bias (including time-consistent households) tend to adopt regular refinancing with no reduction in closing costs.

We further show that, compared to those that choose regular refinancing, households that choose reduced-cost refinancing require a lower interest drop and thus prepone refinancing. Overall, present bias drives divergent refinancing decisions in both the product selection and the timing of refinancing, which provides a unified explanation of the existing puzzles in refinancing mistakes.

We then bring the model to the real-world refinance choices in the 2010-2019 period. Specifically, we examine the use of lender credits and refinance choices. We start by documenting stylized facts about the use of lender credits and their consequences on mortgage rates. We then analyze the matched pairs of home purchase and refinance data, and verify the predictions of our model. We find that a significant share of households choose reduced-cost refinancing, which lowers the closing cost while increasing the mortgage amount for subsequent interest payments. This provides a perfect real-world setting to test our model. A natural explanation for adopting reduced-cost refinancing is that these households face severe liquidity constraints; namely, they cannot afford to pay closing costs out of pocket. We propose an alternative channel that potentially affects refinancing choices across a broader range of households, extending beyond those facing severe budget constraints. Besides, this

[1] See Section 2.2 for the precise definition of present bias.

past decade has witnessed large housing market growth, meaning the liquidity issue should be relatively easy to solve by tapping into the housing equity. More importantly, we find that households that adopt different refinancing products exhibit systematic differences in the timing of refinancing, which cannot be explained by liquidity constraints alone.

The current paper builds on the classic literature on mortgage decisions as a function of payment savings and option value of future refinancing. Stanton (1995) and Stanton and Wallace (1998) pioneered the study of the optimal refinancing choice by rational agents and the implications on differentiated mortgage menu provision. Agarwal et al. (2013) incorporates the option value of refinancing and gives a closed-form solution of the optimal mortgage refinancing threshold. Our paper departs from Agarwal et al. (2013) in two key ways: (i) by incorporating heterogeneous present bias, and (ii) by introducing reduced-cost refinancing. To capture present bias, we adopt the continuous-time hyperbolic discounting model proposed by Harris and Laibson (2013). Present bias accounts for the prevalent inaction in refinancing that remains unexplained by the rational refinancing model. The basic mechanism is as follows. Under present bias, the refinance costs loom larger to households; they thus require a larger interest drop to justify the refinancing action.

The latest research adds further details to the decision model of mortgage refinance. Andersen et al. (2020) use data from Danish mortgage market to estimate psychological cost of refinancing choice. In their paper, the cost of refinancing is the sum of the monetary cost and the psychological cost—which is assumed to be a linear function of household characteristics. By this reduce-form approach, they reveal how psychological costs, and thus refinance decisions, vary with socioeconomic status of households. In comparison, we make further behavioral restrictions on household financial choices and seek to pin down the nature of psychological costs. Instead of allowing for all sorts of unexplained sources of behavioral frictions, we isolate the impact of present bias to refinancing choices. We show that the psychological cost of present bias interacts with the monetary cost—households that are highly present-biased tend to be more sensitive to changes in monetary cost.

Our paper also contributes to the understanding of mortgage refinance choices. Deng and Quigley (2006) point out that irrational refinance behaviors are prevalent and propose a model to better predict prepayment rates. Johnson et al. (2015) use survey data and pre-approved letters as field experiments. They show that more than 50% households do not refinance, and provide explanation through time preference and financial incentives. This is the "omission" error of mortgage refinance. Similarly, Keys et al. (2016) documents that about 20% of households fail to refinance, which could have saved them $160 per month. On the other hand, there is also evidence of households refinancing too quickly, known as "commission error" (Berger et al., 2024). These studies empirically establish the presence and magnitude of people's mortgage refinancing errors, and typically use reduce-form regression to explain the observed errors by borrower characteristics and mortgage characteristics. Zhang (2022) discusses the general equilibrium effect of cross-subsidization between borrowers with high and low refinance inertia. Gerardi et al. (2023) document that minority borrowers face significant barriers to refinance during periods of falling interest rates, resulting in these groups benefiting less from monetary policy-driven rate declines

compared to white borrowers. Our work theoretically establishes and empirically measures the impact of present bias in mortgage refinance decisions in the updated sample.

Our analysis on the use of lender credits join the discussion about the multidimensional features of mortgage products. The literature on mortgage lender credits reveals a complex financial mechanism that allows borrowers to offset closing costs in exchange for accepting a higher interest rate. Agarwal et al. (2017) show that homeowners frequently overpay for mortgage points (upfront fees that reduce interest rates), which suggests they consistently misjudge how long they will maintain their mortgages before refinancing or selling their homes. Woodward and Hall (2010) and Woodward and Hall (2012) find that consumers often overpaid for broker services due to information asymmetry and confusion about fee structures. However, academic attention to these other features of mortgage contracts remains relatively limited compared to mortgage rates itself. As financial intermediaries compete among all these dimensions, understanding how the use of lender credits decisions are made becomes crucial for informed policy decisions.

Finally, our paper contributes to the general literature on applying behavioral models to household finance decisions. Maturana and Nickerson (2019) find a strong peer effect in mortgage refinance choices, both on refinance or not and which lender to finance with. Kuchler and Pagel (2020) use credit card borrowing activities and measure the magnitude of present bias in household financial decisions. Botsch and Malmendier (2020) inspect the influence of personal inflation experiences on aversion to adjustable rate mortgages which leads to significant overpay. Better understanding of household choices in mortgage market also benefits macro policy makers. Maxted et al. (2025) find that present biased households procrastinates in refinancing their mortgages, reducing the effectiveness and speed of this monetary policy transmission mechanism. Our results suggest present bias can explain frictions in mortgage refinance, and financial products can be designed to cater to the decision process present-biased agents to effectively fulfill the goal of policy-makers.

The rest of this paper proceeds as follows. Section 2.2 presents the theoretical model and derives its implications. Section 2.3 describes the dataset that we use, tests stylized facts about inaction in refinance with updated data, and explores factors that correlate with inaction in refinance. Section 2.4 introduces our new way to identify the usage of lender credits in FHA mortgage refinances, and tests our model implications. Section 2.5 calibrates our theoretical model with empirical moments. Section 2.6 concludes.

2.2 Theoretical Framework

To incorporate present bias in households' mortgage refinancing decisions and guide empirical tests, we start with a theoretical model. In the model, a household decide whether to refinance mortgage, weighing the gain from the current mortgage interest drop against its option value and transaction cost under present bias. The target of this section is to derive

the threshold $\Delta < 0$ such that the household refinances as long as the drop in interest rates exceeds the threshold. We focus on how this threshold Δ is affected by present bias.

Model Setup

Macroeconomic Variables Let r denote real interest rate for mortgage, π denote inflation rate, and $i = r + \pi$ denote nominal interest rate. Assume the dynamics of these economic variables as

$$dr = \sigma_r dZ_r,$$
$$d\pi = \sigma_\pi dZ_\pi,$$

where Z_r and Z_π are two Brownian motions with covariantion $\sigma_{r\pi}$. Denote by $\delta \in \mathbb{R}$ the drop in nominal interest rates, which is given by

$$\delta \equiv i - i_0 = r + \pi - r_0 - \pi_0.$$

Therefore, the dynamics of the nominal interest rate drop is as follows:

$$d\delta = \sigma dZ,$$

where $\sigma = \sqrt{\sigma_r^2 + \sigma_\pi^2 + 2\sigma_{r\pi}}$ and Z is a Brownian motion.

Mortgage Value and Repayments. Denote by M_t the real value of outstanding loan balance at time t. In reality, M_t may decline over time for the following three reasons: (i) regular drops in the nominal loan balance due to fixed-rate mortgage payments; (ii) a possible prepayment of entire mortgage balance due to relocation; (iii) a continuous depreciation of the mortgage obligation due to inflation. Following Agarwal et al. (2013), for tractability we structure mortgage repayment as a Poisson process such that the real value of the mortgage remains constant until an exogenous Poisson repayment event.[2] The arrival rate of the Poisson repayment, denoted by $\lambda > 0$, captures those three sources of mortgage value decline described above. Hence, the dynamics of the mortgage real value without exercising the refinance option can be characterized as

$$M_0 = M,$$
$$dM_t = -M dP$$

where M denotes the constant real mortgage value before repayment, and P is a Poisson process with the arrival rate λ. The loan is paid in full once the Possion jump happens.

[2]With this modeling technique, we do not need to keep track of time to maturity and changes in mortgage value over time, which greatly simplifies dynamic programming. Agarwal et al. (2013) show that the analytical solution by assuming constant mortgage real value until a Poisson repayment event is close to numerical results considering the change in the mortgage value before maturity.

Therefore, the refinance choice is made conditional on the Possion jump has not occurred yet, and the continuous flow of real interest payments for the mortgage (before the Poisson repayment) is $(i_0 - \pi)M$.

Dynamic Choice in Refinancing. Denote the transaction cost of refinancing by $C(M)$. At any time before the Poisson repayment event, the household faces the decision of whether to refinance, trading off the reduced interest payments against the transaction cost and the option value of refinancing. They have the following two refinancing options:

Option I: Pay closing cost $C(M)$, and the subsequent flow interest payments iM;
Option II: Pay closing cost $C(M) - l$, and the subsequent flow interest payments $i'(M + l)$, where $l \in (0, C(M)]$ and $i' > i$. This option amounts to zero-cost refinancing if $l = C(M)$.

Household makes refinancing decisions in two phases. They first decide *what* refinancing option they would adopt—if they ever refinance—to minimize the overall mortgage refinancing payments given their time preferences. Fixing their preferred refinancing option, they then decide *when to* refinance according to the interest rate dynamics. Let $\Delta < 0$ be a threshold such that the household decides to refinance once the nominal interest rate change exceeds the threshold (i.e., $\delta = i - i_0 < \Delta$).

Following Harris and Laibson (2013), we specify the household's discount factor at time t when evaluating interest payments at time $s \geq t$ as

$$D_t(s) = \begin{cases} 1 & \text{for } s = t, \\ \beta e^{-(\rho+\lambda)(s-t)} & \text{for } s > t, \end{cases} \tag{2.1}$$

where $\rho > 0$ denote the household's general instantaneous discount factor and $\beta \in (0, 1]$ captures present bias. Note this specification embeds the classic exponential discounting when $\beta = 1$ (no present bias) and $\lambda = 0$ (no mortgate value decline). Recall that the loan is paid in full once the Poisson repayment event occurs. Therefore, the effective discount rate is increased by the Poisson arrival rate λ. To see the role of present bias (i.e., $\beta < 1$), as opposed to the classic exponential discounting, the discount factor now features an immediate discrete drop (See Figure 2.1). This implies that all future payoffs are further discounted by $\beta < 1$, thus capturing the notion of present bias.

Analysis

What Refinancing Option is Preferred

We first analyze what refinancing option households prefer, if they ever choose to refinance at present. Compared to Option I, Option II features a reduced closing cost, which increases the subsequent interest payments. A household with present bias β and effective discount rate $\delta + \lambda$ prefers Option II if

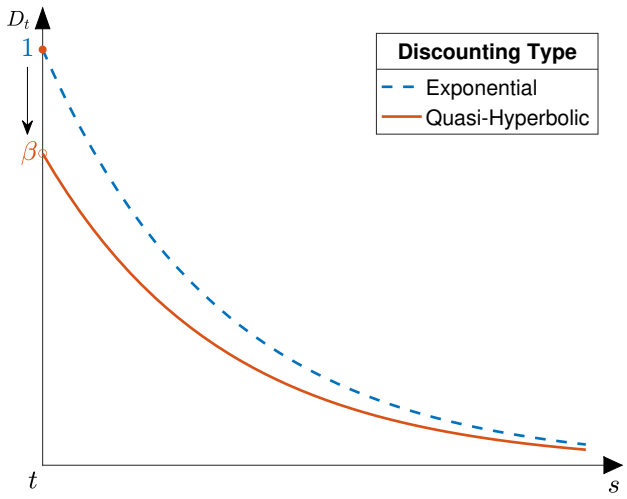


Figure 2.1: Discount Factor Evaluated at t

$$C(M) + \int_0^\infty \beta e^{-(\rho+\lambda)t} iM\mathrm{dt} > C(M) - l + \int_0^\infty \beta e^{-(\rho+\lambda)t} i'[M+l]\mathrm{dt}$$

That is,

$$\beta < \bar{\beta} \equiv \frac{\iota(\rho+\lambda)}{i'(1+\iota) - i},$$

where $\iota = l/M$.

Proposition 1. *If $\beta < \bar{\beta}$, then the household chooses the refinancing Option II.*

Proposition 1 implies that, if $\bar{\beta} = \iota(\rho+\lambda)/[i'(1+\iota) - i] > 1$, then all households choose the reduced-cost refinancing. Therefore, if Option I and Option II are both chosen by some households, then we have $\bar{\beta} \leq 1$. In this case, time-consistent households prefer Option I, and only households that are sufficiently present-biased (i.e., $\beta < \bar{\beta} \leq 1$) prefer Option II.

Corollary 1. *If Option I and Option II are both chosen by some households, then time-consistent households choose Option I, and only sufficiently present-biased households ($\beta < \bar{\beta}$) choose Option II.*

Refinancing Threshold for Option I

Given present bias and the chosen refinancing option, We now derive the refinancing threshold $\Delta < 0$ for the household. The following theorem states the main result of the paper, characterizing the optimal refinancing threshold for any present bias $\beta \in (0, 1]$ and closing cost $C(M) \in [0, M]$.

Jibberish 1 (Mortgage Refinancing with Present Bias)**.** *For any household with present bias* $\beta \in (0, 1]$*, the optimal policy is to refinance when*

$$i - i_0 \leq \Delta \equiv \delta(\beta) = -\frac{1}{\psi}[\phi + W_0(-e^{-\phi})], \tag{2.2}$$

where $W_0(.)$ *is the principal branch of the Lambert* W*-function,*

$$\psi = \frac{\sqrt{2(\rho+\lambda)}}{\sigma},$$
$$\phi = 1 + \psi(\rho+\lambda)\frac{C(M)}{\beta M}.$$

Note that Theorem 1 nests the optimal threshold characterization in Agarwal et al. (2013) for time-consistent households (i.e., $\beta = 1$). Present bias distorts a household's refinancing timing by amplifying their perceived closing cost—from the objective cost $C(M)$ to the subjective cost $C(M)/\beta$. Therefore, fixing the refinancing option, present-biased households perceive a higher closing cost and thus are more reluctant to refinance. This result explicitly derives the psychology cost measured in Andersen et al. (2020) through the channel of present bias. Further, compared to Andersen et al. (2020) where the overall cost of refinancing is the sum of the objective cost and the psychology cost, our result highlights how the objective factor and behavioral frictions interact with each other. In this vein, present-biased households are more sensitive to variations in closing costs.

Here we provide an approximate refinancing policy without the Lambert W-function. Define

$$f(x) = e^{\psi x} - \psi x - 1 - \psi(\rho+\lambda)\frac{C(M)}{\beta M}.$$

Take second-order Taylor approximation of $f(x)$ around $x = 0$, we have

$$\begin{aligned} f(x) &\approx f(0) + f'(0)x + \frac{1}{2}f''(0)x^2 \\ &= -\psi(\rho+\lambda)\frac{C(M)}{\beta M} + 0 + \frac{1}{2}\psi^2 x^2. \end{aligned}$$

Since $f(\Delta) = 0$ by Equation B.24, we have $-\psi(\rho+\lambda)\frac{C(M)}{\beta M} + \frac{1}{2}\psi^2 x^{*2} \approx 0$, and thus

$$\Delta \approx \hat{\delta}(\beta) = -\sqrt{\frac{2(\rho+\lambda)C(M)}{\psi\beta M}} \tag{2.3}$$

where $\psi = \frac{\sqrt{2(\rho+\lambda)}}{\sigma}$.

Refinancing Threshold for Option II

Define the equivalent interest rate for the reduced-cost refinancing Option II to be

$$\tilde{i} = \frac{i'(M+l)}{M}.$$

As an analogy to Theorem 1 and its second-order Taylor approximation, households that chose Option II refinance when

$$\tilde{\Delta} = \tilde{i} - i_0 \approx -\sqrt{\frac{2(\rho+\lambda)[C(M)-l]}{\psi\beta M}}.$$

For any reduced cost refinancing $l < C(M)$, the required equivalent interest rate drop to refinance grows as present bias exacerbates. For zero-cost refinancing where $l = C(M)$, $\tilde{i} = i_0$; that is, households require the nominal interest rate drop to be approximately

$$i' - i_0 \approx \frac{M}{M+l} i_0 - i_0 = -\frac{l}{M+l} i_0 < 0.$$

By Proposition 1, households choose the regular refinancing Option I if and only if they exhibit sufficiently low present bias; that is, $\beta \in (\bar{\beta}, 1]$. Therefore households that chose Option I require greater interest rate drop compared if

$$-\sqrt{\frac{2(\rho+\lambda)C(M)}{\psi M}} < -\sqrt{\frac{2(\rho+\lambda)[C(M)-l]}{\psi\beta M}},$$

where $\beta < \bar{\beta}$. That is,

$$\frac{l}{C(M)} > 1 - \beta.$$

Proposition 2. *If the reduced cost in Option II is sufficiently large—namely, $l/C(M) > 1-\beta$—then the required interest rate drop to refinance using Option I is greater than its equivalent counterpart to refinance using the reduced-cost Option II.*

Corollary 2. *Fix a sufficiently large interest rate drop $\delta = i - i_0 < \hat{\delta}(\bar{\beta})$ where $\hat{\delta}(\cdot)$ is given by (2.3). There exists $\underline{\beta} \in (0, \bar{\beta})$ such that*

1. *households with large present bias $\beta \in (0, \underline{\beta})$ will not refinance;*
2. *households with moderate present bias $\beta \in (\underline{\beta}, \bar{\beta})$ refinance using the reduced-cost refinance Option II;*
3. *households with small or no present bias $\beta \in (\bar{\beta}, 1]$ refinance using Option I.*

2.3 Procrastination in Mortgage Refinance

So far we have discussed how a present biased agent would make mortgage refinance choices. In this section we examine actual refinancing decisions to test our model of mortgage refinance inaction driven by present bias. By analyzing real refinancing choices we can directly measure how present bias explains observed frictions in mortgage refinance choices. We first describe the data set we use, then analyze the presence of inaction in refinance with newly updated data, and discuss factors related to inaction in refinance.

Data

The core of this analysis relies on Black Knight McDash mortgage servicing data (hereafter referred to as the McDash data). The McDash data provides comprehensive mortgage performance and servicing information covering approximately 80% of U.S. mortgages. This dataset includes critical variables such as date of origination, loan amount, interest rates, credit scores, property values, zip code of the property location, Loan-to-Value (LTV) ratios, and product types, while tracking monthly mortgage performance until prepayment or foreclosure.

To overcome the McDash data's limitation of loan-level anonymizationâ€"which prevents direct identification of which new loans prepay old loans during refinancing- We merged it with ATTOM recorder data using overlapping variables and a statistical-learning algorithm, following Bartlett et al. (2021). The ATTOM data provides property transaction records and lender identities from local recorder and assessor offices, along with essential property characteristics needed for counterfactual market price estimation, including location, bedroom and bathroom counts, square footage, and construction year.

Additional mortgage application information and information about underwriting fees come from Home Mortgage Disclosure Act (HMDA) data. HMDA data covers approximately 90% of U.S. mortgage originations and contains mortgage application. HMDA is managed by Consumer Financial Protection Bureau (CFPB). CFPB requires every monitored mortgage underwriter to report relevant information during the mortgage application process. These information include borrower race, ethnicity, gender and others. Since 2018, HMDA also reports how much is the underwriting cost. It worth pointing out that although HMDA reports mortgage points and lender credits, existing research argues the data quality is not good enough to draw robust conclusions from these fields (Bhutta and Lambie-Hanson, 2024). We will address this issue and propose an alternative approach to identify the use of lender credits.

Inaction in Mortgage Refinance Revisited

We revisit the results about failure to refinance discussed in Keys et al. (2016) with updated data for the most recent interest rate decline event in 2020-2022. We find that inaction in refinance persist for the recent decade.

Table 2.1 summarize the variables of interest regarding inaction in refinance. Despite historically low mortgage rates of around 2.8% in 2022, a substantial number of borrowers have not refinanced their mortgages. The data shows that 31 million GSE loans (45%) and nearly 6 million FHA loans (38%) remained active. These non-refinanced loans carry significantly higher interest rates compared to market rates, with GSE loans averaging 3.8% and FHA loans averaging 4.1%. This represents a potential missed opportunity for substantial savings, particularly for FHA borrowers who maintain higher interest rates despite having reasonably good credit scores (679 on average). The property value in this period has been growing substantially so the equity required for refinance should not be a major concern. The persistence of these higher-rate loans suggests that barriers to refinancing have not decreased since academic attention and policy interventions.

Figure 2.1 plots the distribution of mortgage rates for all loans and loans with credit score greater than 680 at origination, conditional on the loan is still active (not being prepaid) by January 2022. The red dashed line represents the average mortgage rate during 2022, about 2.8%. Most of these borrowers are overpaying on their mortgage. Considering that that the mortgage rate has been at a historical low level and is approaching the 0 lower bound of interest rates (in fact, the short rate for rate for this period is already at the 0 lower bound), it will be very difficult to attribute inaction in refinance to overestimation of the option value to refinance later. We believe the present bias channel and increased upfront cost as discussed in our model would be a more reasonable explanation.

Factors Correlates with Inaction in Refinance

What factors explain this persistent inaction in mortgage refinance even at historical low interest rate period in 2022? Table 2.2 shows the regression results for the following regression:

$$\text{NoRefinance}_{ict} = \alpha + \beta_1 \text{CreditScore}_i + \beta_2 \text{LTV}_i + \beta_3 \text{InterestRate}_i + \beta_4 \text{PropertyValue}_i + \gamma_c + \delta_t + \epsilon_i \tag{2.4}$$

$NoRefinance_{ict}$ is a dummy variable indicating a purchase loan originated after January 2009 has never been refinanced before January 2022.for borrower i in county c at time t. β_1 through β_4 are the coefficients for loan characteristics that we are concerned about: Credit Score, LTV, Interest Rate and Proerty Value. γ_c represents locational fixed effects at county level and δ_t represents time fixed effects at quarter level, which captures unobserved factors that are explained by time and location that are correlated to refinance decisions. ϵ_i is the error term.

Together with the regression result, Figures B.1 and Figure B.2 show bin-scattered plots of the relationship between inaction in refinance with respect to credit score and LTV. These results suggest several key factors influence mortgage refinancing behavior across different loan types. Borrowers with stronger credit background and start with higher interest rates are more likely to take advantage of refinancing opportunities. Loan-to-value ratios and property value matter significantly for conventional GSE and FHA loans but have relatively small impact on Jumbo loans. These results are consistent with Andersen et al. (2020)

which suggests certain borrowers sharing similar characteristics face more challenges in the refinancing decisions, and this result is persistent over time and across different countries.

2.4 Lender Credits in Mortgage Refinance

So far we have discussed theoretically how a present biased agent would make mortgage refinance choices, and inaction is still prevalent among mortgage borrowers. In this section we focus on mortgage refinances that used lender credits, and introduce new stylized facts about lender credits. We then examine how refinancing decisions with and without lender credits are intrinsically different, using matched individual choices from 2009-2019 to test our model. By linking and analyzing the purchase and refinance mortgages we can directly test the implications on decision rules and refinance timing for present biased agents.

Lender Credits

Mortgages are multi-dimensional contract that allows credit rationing through different channels. Specifically, borrowers can choose to pay more upfront, also known as using "points", to reduce their mortgage rates. Stanton and Wallace (1998) first developed the model to show how mortgage points can signal the credit profile of borrowers and achieve a separate equilibrium for borrowers into different rates. Lender credits, on the other hand, works the other way around, like "negative points". Borrowers choose to borrow more upfront, and lenders tend to adjust the mortgage rate to a higher level to account for the increased default risk corresponding to the lower equity on the home balance sheet as well as signals related to low credit worthiness.

Lenders constantly advertise for the "zero-cost" refinance products [3]. But essentially choosing this product means borrowers are using lender credits to the extent that lender credits covers all of the upfront costs related to refinance. This inevitably leads to an increase in their future mortgage payment, because both the loan amount and the mortgage rate have increased. Here we observe a trade-off between an upfront payment and a series of future payments, with the sum of future payments being much higher than the alternative upfront payment. Examining refinancing decisions using lender credits provides an accurate setting to test whether present bias models explain refinance choices.

Our test will compare refinancing rates between borrowers using refinancing options without using lender credits versus those refinanced with lender credits. By controlling for borrower characteristics, loan terms, and market conditions, we can identify how refinance time and interest rate gap differs between the two groups.

Ideally, we would like to observe to what extend the borrowers are using lender credits. The HMDA data starting from 2018 provides additional field documenting the use of lender credit. However the measure does not capture the full amount of refinance cost that are

[3] https://www.consumerfinance.gov/ask-cfpb/is-there-such-a-thing-as-a-no-cost-or-no-closing-loan-or-refinancing-en-141/

borrowed into loan balance. Here is the definition of lender credits from Bhutta and Lambie-Hanson (2024):

> This field captures rebates from the lender that can help borrowers offset their closing costs. ... HMDA only includes general credits listed at the bottom of the Closing Disclosure in Box J. Lenders may also provide credits to pay for specific closing items; such credits would be listed in the "Paid by Others" column of the Closing Disclosure. As a result, those credits–and the expenses they are offsetting–would not be observed directly in HMDA data.

Identifying Use of Lender Credits for FHA Refinances

Instead of directly measure the use of lender credits, we take an alternative approach to identify the use of lender credits by harvesting a feature of the FHA mortgages.

FHA aims to increase homeownership accessibility, particularly for first-time and low-to-moderate income buyers, by insuring mortgages with more lenient credit requirements compared to conventional mortgages. As the subprime mortgage market collapsed during the 2008 financial crisis, FHA-insured loans experienced a surge in popularity. FHA mortgages account for 28.1% of total home purchase loan amount (32.6% of loan count) in 2009, according to U.S. Department of Housing and Urban Development calculations. Borrower can purchase a house with LTV of up to 96.5% (3.5% down payment), compared to the 80% (20% down payment) requirement for conventional Government Sponsored Enterprise (GSE) mortgages.

FHA prohibits the mortgage amount to exceed 96.5% of the property value. But we do observe LTV greater than that in the data. This happens because these borrowers use lender credits to cover closing costs. In this section we demonstrate how we identify use of lender credits by focusing on FHA refinances that have a LTV greater than 96.5%.

To illustrate the validity of this method, we first show the LTV exceeding 96.5% for FHA mortgages indeed indicates the origination costs are financed.Table 2.3 summarizes the key characteristics of all FHA refinances and FHA refinances with LTV greater than 96.5% in 2019. Here we want to reinstate that the measure of "lender credits" is very noisy and inconsistent with other evidence, validating the quote above. As a result we are not conducting analysis with the lender credits reported in this table. Figure 2.2 plots the relationship between LTV and origination costs for FHA mortgages in 2019. As shown in the figure, the relationship between LTV and total loan costs are linear and approximately 1 for 1. The relationship is not perfectly 1 for 1 because borrowers can choose to finance part of the origination costs to loan amount. This results indicates the LTV exceeding 96.5% can be used as a valid proxy to measure the use of lender credits for FHA borrowers.

How does the use of lender credits affects the mortgage rate? Figure 2.3 plots the interest rate and LTV. As borrowers use more lender credits, their mortgage rate increases to a higher level. In an linear model, an an increase 1% in LTV corresponds to an increase of 0.1% in the the mortgage rate. Figure 2.4 further decomposes this relationship for different lenders.

Compared to banks and credit unions, nonbank lenders both exhibit higher interest rate and LTV, indicating that they are charging higher costs and borrowers are borrowing more to cover these costs.

The Use of Lender Credits and Refinance Choices

So far we explored the characteristics of the population of lender credits users using the new HMDA data. However, to better understand the choice of using lender credits, and understand how change in upfront cost affect refinance decision rules, we need to match the refinance loan with the original purchase loan, so that we can observe the rate gap and time difference between purchase loan and refinance loans. This observation is particularly relevant to test present biased models because it represents a revealed preference for trade-off between immediate costs and future costs. When borrowers choose this option despite the higher lifetime cost, it provides evidence of present-biased decision-making in high-stakes financial contexts.

We first test the same patterns that FHA loan LTV at refinance can indicate the use of lender credits apply to the ATTOM-McDash merged sample. Table 2.5 summarized the use of lender credits in this matched sample. Compared to Table 2.3, the distribution of LTV and sample size are approximately comparable. The rate difference between two groups also shares similar patterns.

Next, we test the use of lender credits and the predictions of present bias models. Figure 2.5 plots the frequency of FHA refinances with and without use of lender credits from 2010-2019. We observe distict patterns for refinance choices for different groups, relative to the mortgage rate changes.

The interest dynamics as shown in the graph features several periods with different interest rate dynamics. Roughly January 2009 to July 2013 features a sequence of monetary policy interventions that the Federal Reserve has taken as a response to the Great Financial Crisis. Quantitative Easing 1 (QE1) began during the financial crisis, running through March 2010, followed by QE2 which was effectively initiated in September 2010 when the Fed signaled its intentions, though formally operating from November 2010 until June 2011. In September 2011, the Fed launched the Maturity Extension Program (MEP), which involved trading approximately $600 billion in shorter-term Treasury securities for longer-term ones to reduce long-term interest rates. The final major intervention, QE3, commenced in September 2012 and continued until the Fed began tapering in June 2013, following Bernanke's announcement on May 22, 2013. Later in 2015-2016, mortgage rates declined significantly again due to the response to global capital flight to safety and US domestic economic growth concerns by the Federal Reserve. But the magnitude has been smaller compared to the mortgage rate change from 2009-2013. In later sections we would like to focus on the QE periods, because the mortgage rate changes are more significant and policy communications are clearer.

Borrowers with and without credit use exhibit different patterns in the mortgage rate during the periods when interest rate was declining. Borrowers who used lender credits were mainly refinancing earlier in each of the interest rate declining periods, specifically during

the end of 2010 and the beginning of 2015, featuring the first significant decrease in the mortgage rates. However, borrowers who did not use lender credits were mainly refinancing later in each of the interest rate cycles, specifically, during mid 2013 and early 2017. Figure 2.7 plots the histogram of time from purchase to refinance for the groups with and without lender credits. This difference in refinance time is persistent across the refinance time, as shown in Figure 2.7.

This difference in time reveals a more important feature predicted by our model, that the decision rule in refinance depends on upfront cost for present biased borrowers. Figure 2.8 plots the mortgage rate difference between purchase and refinance loans. On average, borrowers used lender credits refinance when the mortgage rate decreased by 89 basis points, while borrowers did not use lender credit refinance when the mortgage rate decreased by 113 basis points.

FHA loans are subject to the Mortgage Insurance Premium (MIP) which also experienced change during the sample period (Liu (2024)). Figure 2.9 plots the mortgage rate difference after controlling for the change in FHA MIP. The conclusion that on average borrowers used lender credits refinance faster when rate change hits a smaller gap still holds.

As reported in Table 2.7, after controlling for location-fixed effects and borrower characteristics, the use of lender credits corresponds to 204 bp higher in the gap between purchase loan and refinance loan. This means borrowers using lender credits saved 204 bp less compared to the borrowers who did not use lender credits. There are two channels contributing to the difference in mortgage rate. First, for present biased agents, removing upfront costs of refinance makes their decision rules easier to trigger, they refinance ealier during the period when interest rate is declining, and missing the chance to refinance at a lower rate later. Second using lender credits itself increases default risk and signal worse credit profile to the lenders, thus their mortgage rate increased relative to refinances without the use of lender credits.

We extend our sample to the latest years from 2019 to 2022, when COVID shock and the Federal Reserve reduce interest rate to a historically low level. The results are presented in Figure B.3. We observe a similar pattern where households who use lender credits refinance earlier in this cycle and refinance at a higher mortgage rate compared to borrowers who did not use lender credits. Due to data restrictions we are currently not able to match the refinance loan with original purchase loan, so the results include loans originated before January 2019. But the main conclusion is not affected because most of the loans originated before 2019 are likely to have refinanced in previous low interest rate periods.

Which borrowers are more likely to use lender credits when refinance? We run the fullowing regression:

$$\text{UseCredits}_{ict} = \alpha + \beta_1 \text{LoanFeatures}_i + \beta_2 \text{BorrowerFeatures}_i + \beta_3 \text{LenderFeatures}_i + \gamma_c + \delta_t + \epsilon_i \tag{2.5}$$

Where $UseCredits_{ict}$ is a dummy variable indicating an FHA refinance has LTV greater than 96.5%, indicating lender credits were used for borrower i in county c at time t. β_1 through β_3 are the coefficients for factors that we are concerned about: Credit Score, LTV, Interest Rate and Proerty Value as Loan Features; DTI, race as Borrower Features; Lender

Type (Bank, Nonbank and Credit Unions) and whether the refinance loan is originated by the same lender that originated the purchase loan. γ_c represents locational fixed effects at county level and δ_t represents time fixed effects at quarter level, which captures unobserved factors that are explained by time and location that are correlated to refinance decisions. ϵ_i is the error term.

Table 2.4 used HMDA data and shows the regression result that explores factors explaining the use of lender credits among FHA borrowers. Larger loan amounts decrease the likelihood of using lender credit. Black and Hispanic borrowers significantly more likely to use lender credits compared to White borrowers, while Asian borrowers are slightly less likely. Use of lender credits generally increases with Debt-to-Income (DTI) ratios and decreases with age. Table 2.6 used ATTOM-McDash Matched data confirmed the same results, and additionally indicates that borrowers who worked with the same lender where they obtained their purchase loan are more likely to use lender credits.

2.5 Apply Present Bias Model to Use of Lender Credits

We have discussed theoretical predictions of agents making mortgage refinance choices and empirical patterns of how the use of lender credits affect refinance choices. In this section, we bridge the gap between model and data and match parameters in the models with empirical moments.

Empirical results indicate that borrowers who refinance with and without the use of lender credits shall refinance with a different rule, specifically the required decrease in mortgage rate is lower for refinance with the use of lender credits. Our model provides a closed form solution for how much this gap should be:

$$\Delta \approx -\sqrt{\frac{2(\rho+\lambda)C(M)}{\psi\beta M}}$$

$$\tilde{\Delta} = \tilde{i} - i_0 \approx -\sqrt{\frac{2(\rho+\lambda)[C(M)-l]}{\psi\beta M}}.$$

Where Δ is the required decrease in mortgage rate for borrowers without use of lender credits, and $\tilde{\Delta}$ is the required decrease in mortgage rate for borrowers used lender credits.

We chose the following parameters to calibrate our model:

$$\begin{aligned} \beta &= 0.9 \\ l/M &= 2.4\% \\ C(M)/M &= 3.2\% \\ \sigma &= 0.0109 \\ \rho &= 0.05 \\ \mu &= 10\% \end{aligned}$$

The justification of these choices are as follows: We take the present bias parameter $\beta = 0.9$, which indicates a modest time inconsistency problem.[4] Based on HMDA Data in Table 2.3, Mean (median) Loan amount is \$220,000 (\$205,000) and mean (median) upfront cost is about \$ 7,000 (\$6,500). Thus upfront costs are about 3.2% of loan amount. Based on McDash Data reported in Table 2.5, the mean LTV for FHA refinance loan with LTV¿96.5% is 98.9%, meaning on average borrowers use additional credit from their lender to cover about 2.4% of their loan amount, which is 75% of upfront costs. The rest of the parameters, the probability of moving μ, the instantaneous discount factor ρ, and the variation in intereste rate dynamics σ are the same as Agarwal et al. (2013). We updated the average inflation for our sample period to 0.02. The average mortgage rate of loans that were refinance in our sample period i_0 is about 0.05. Thus we have:

$$\lambda = \mu + \frac{i_0}{\exp[i_0\Gamma] - 1} + \pi = 0.140$$

$$\psi = \frac{\sqrt{2(\rho + \lambda)}}{\sigma} = 56.55$$

Pluging in the numbers, we have

$$\begin{aligned} \Delta &= -1.546\% \\ \tilde{\Delta} &= -0.773\% \end{aligned}$$

This result is consistent with the empirical moments we observe for borrowers who purchased their mortgage in 2009-2010 when the mortgage rates are high and then refinanced during the QE period from 2011 to 2013. Figure 2.11 and Figure 2.12 zoom in our findings to this period. This is helpful because we can focus on borrowers choices within one full credit cycle, so that we do not have to make assumptions for borrowers who missed the chance to

[4]Most empirical evidence indicates that short-run discount rates are substantially higher than 10 percent. DellaVigna et al. (2017) estimates $\beta = 0.58$ using a model of job search with reference-dependent preferences. Allcott et al. (2022) estimates β between 0.74 and 0.83 for payday loan borrowers. Laibson et al. (2024) estimates the present bias parameter $\beta = 0.53$ for households' consumption decisions. Gruber and Köszegi (2001) also calibrates present bias as $\beta = 0.9$ for addictive behaviors.

refinance in one cycle and act in later credit cycles. From the figures we can see borrowers who used lender credits refinanced earlier and at a higher rate (less savings), compared to borrowers who did not use lender credits. The amount of interest rate gap is consistent with what our model have predicted: borrower refinanced with lender credits refinanced when interest rate gap is about 0.8%, and borrower refinanced without lender credits refinanced when interest rate gap is about 1.5%. The borrowers who did not use lender credits refinanced later, because the interest rate decline have not reached the level low enough to trigger their refinance threshold. This may cause refinancing too late (or inaction) because the mortgage rate decline may never be large enough to trigger their thresholds. This is especially relevant for borrowers who are more subject to present bias, because an increase in present bias (smaller β) will enlarge the required mortgage rate gap. On the other hand, the Borrowers used lender credits refinanced immediately when the mortgage rate decline hits their threshold. This may cause refinancing too early because they miss the opportunity to refinance at a lower rate. Holding borrowers present bias constant, using lender credits to reduce upfront refinance cost may cause welfare loss due to refinancing at a less optimal rate. But lenders may have incentives to promote reduced or zero cost refinance products since this can be effective in generating more revenue from interest payments.

2.6 Conclusion and Discussions

This paper examines how present bias affects mortgage refinancing decisions, through theoretical modeling and empirical analysis of U.S. mortgage data. Our theoretical model demonstrates that present-biased borrowers require larger interest rate drops to refinance due to their heightened sensitivity to upfront costs. This behavioral friction amplifies the impact of closing costs, effectively increasing the threshold for refinancing action. The model predicts distinct refinancing behaviors: households with severe present bias avoid refinancing entirely; those with moderate present bias opt for reduced-cost refinancing with lender credits; and less present-biased borrowers choose regular refinancing.

Using FHA mortgage data, we identified lender credits usage through loans with LTV ratios exceeding the LTV limit required by FHA. We documented a clear linear relationship between LTV exceeding this threshold and total loan costs, indicating the significant presence of zero or reduced cost refinance products. Increased usage of lender credits correlates with higher mortgage rates.

Analysis of matched mortgage refinance pairs confirmed key theoretical predictions. Borrowers using lender credits refinanced earlier in interest rate cycles but achieved smaller rate reductions compared to those who paid closing costs out of their pockets. After controlling for location-fixed effects and borrower characteristics, the use of lender credits corresponded to a 204 basis point higher gap between purchase and refinance loans. We also identified demographic patterns in lender credits usage. Minority borrowers were significantly more likely to use lender credits compared to White borrowers. Lender credits usage generally increased with debt-to-income ratio and decreased with age.

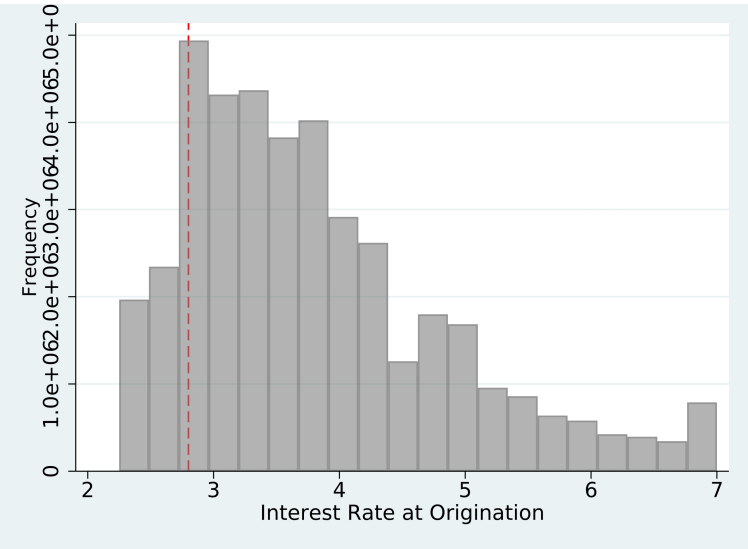
Following the introduction of present biased agent models, structural estimation of magnitude of present bias in household financial decisions could provide quantitative insights into welfare effects. In addition, researchers will be able to evaluate the effectiveness of the interest rate policy transfer, examine the long-term consequences on the accumulation of household wealth, and examine the strategy of mortgage lenders given the preference of the borrower.

Our research demonstrates that present bias can explain financial choices in the selection of mortgage products and time to take actions. Financial intermediaries have responded by developing products like zero cost refinances that cater to present-biased preferences, though these come with long-term tradeoffs. Understanding the mechanism of financial decision making is essential for financial market regulation and policy initiatives to reduce housing wealth inequality.

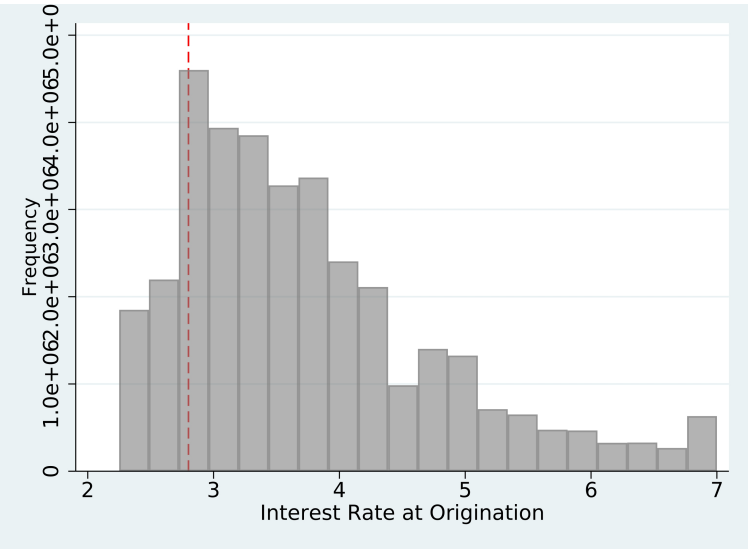
Figures

Figure 2.1: The Scope of Inaction in Refinance

Panel A: All Loans

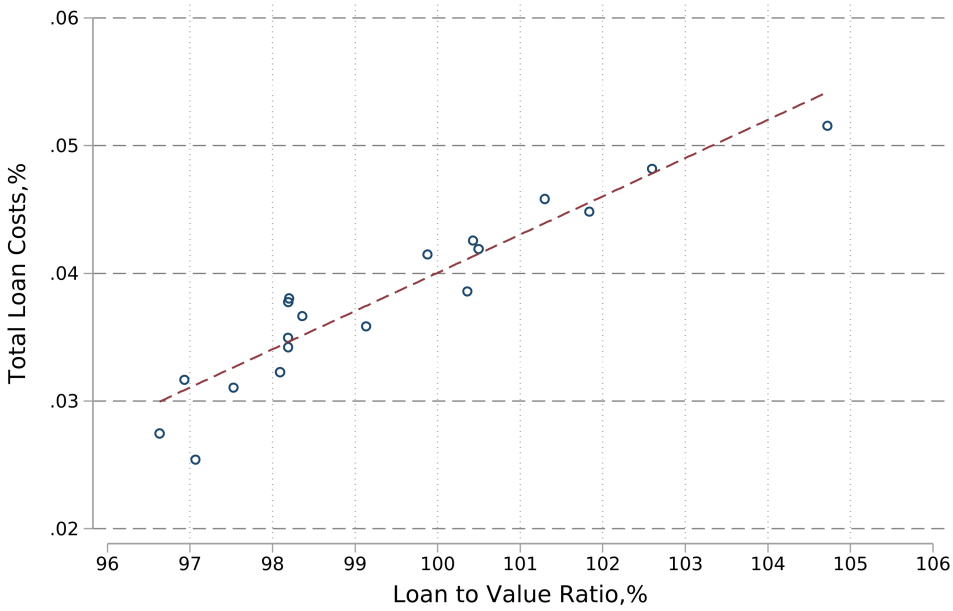


Panel B: Loans with Credit Score¿680



Note: These figures plot the distribution of mortgage rates for loans originated after 2009 and have not been prepaid (remain active) until January 2022. The red dashed line indicates the average mortgage rate in 2021 at about 2.8%. Panel A plots all loans and Panel B plots for loans with Credit Score greater than 680 at origination.
Source: McDash

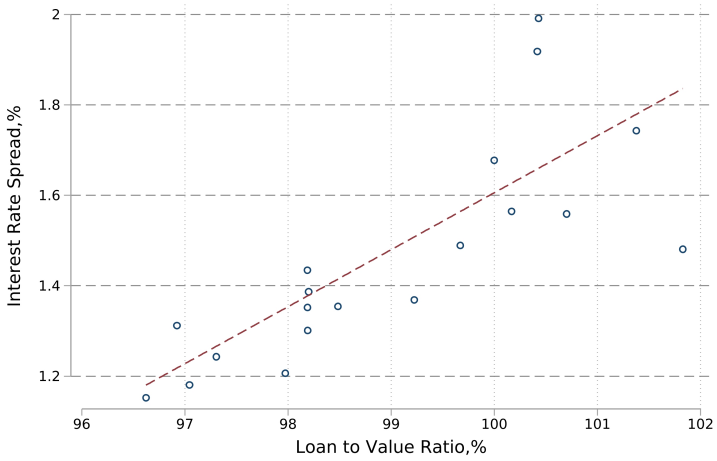
Figure 2.2: Loan Costs and LTV above FHA Threshold



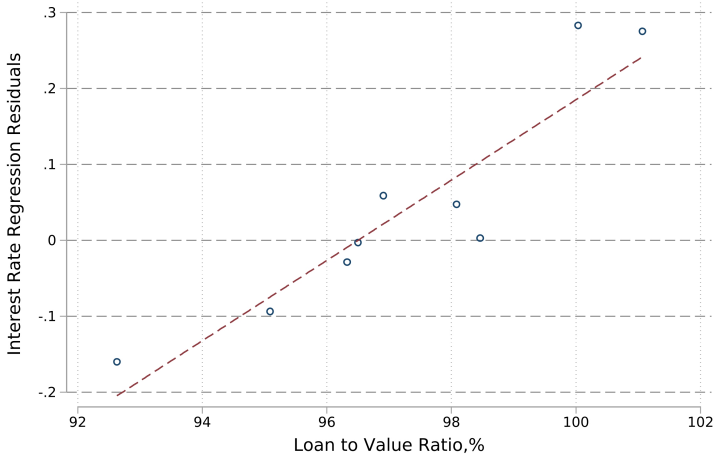
Note: These figures plot the relationship between origination cost and LTV for FHA mortgage origination with LTV greater than 96.5% in 2019. The x-axis shows LTV. The y-axis displays the Total Loan Costs reported in HMDA as percentages of loan amount.
Source: HMDA

Figure 2.3: Mortgage Rate and LTV

Panel A: Interest Rate Spread



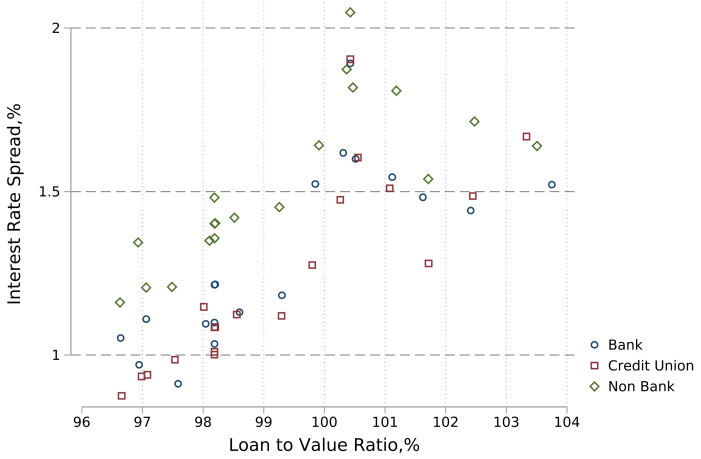
Panel B: Interest Rate Residuals



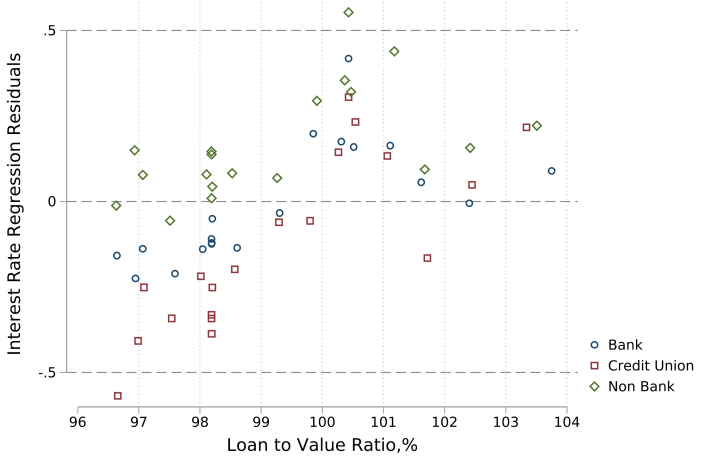
Note: These figures plot the relationship between LTV and interest rate for FHA mortgage refinances in 2019. The x-axis represents LTV. The y-axis on Panel A shows interest rate spread, reported directly in HMDA, defined as the prevailing average prime offer rate available in the market and the rate paid by the borrower. The y-axis on Panel B shows interest rate residuals, which is the residual of a regression of the interest rate reported in HMDA on county, loan amount, DTI, and census tract CRA status.
Source: HMDA, Authors' own calculation

Figure 2.4: Interest Rate and LTV by Lender Types

Panel A: Interest Rate Spread

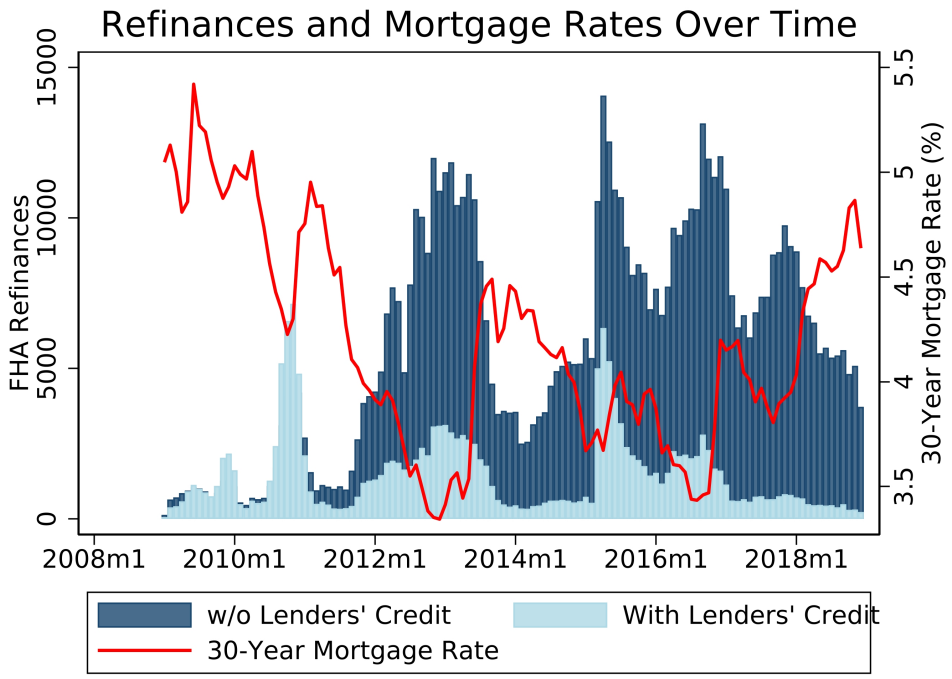


Panel B: Interest Rate Residuals



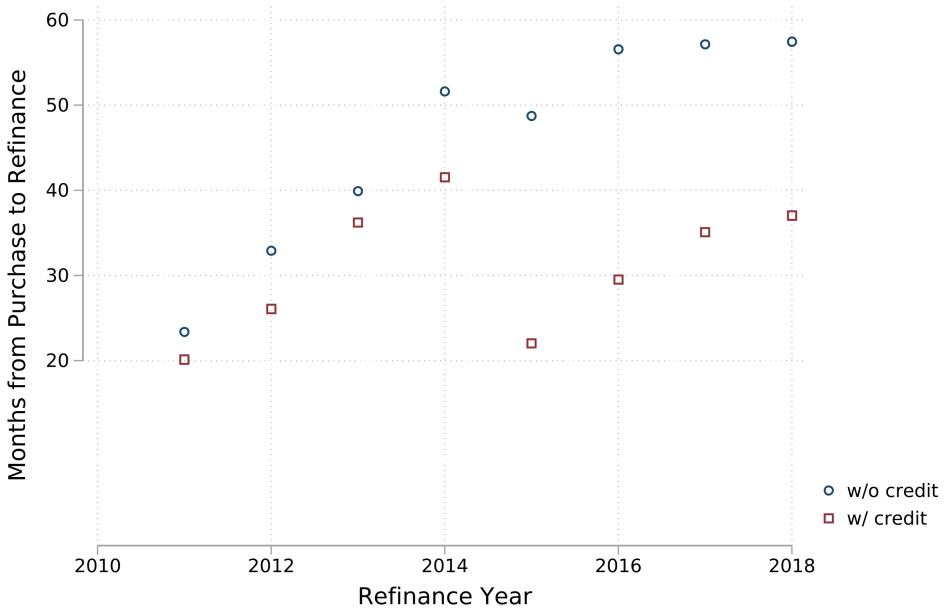
Note: These figures plot the relationship between LTV and interest rate for FHA mortgage refinances in 2019, across lenders: Banks (blue circles), Credit Unions (red squares), and Non-Banks (green diamonds). The x-axis represents the Loan to Value Ratio. The y-axis on Panel A shows interest rate spread, reported directly in HMDA, defined as the prevailing average prime offer rate available in the market and the rate paid by the borrower. The y-axis on Panel B shows interest rate residuals, which is the residual of a regression of the interest rate reported in HMDA on county, loan amount, DTI, and census tract CRA status.
Source: HMDA, Authors' own calculation

Figure 2.5: Frequency of FHA Refinances and Mortgage Rate, 2009-2019



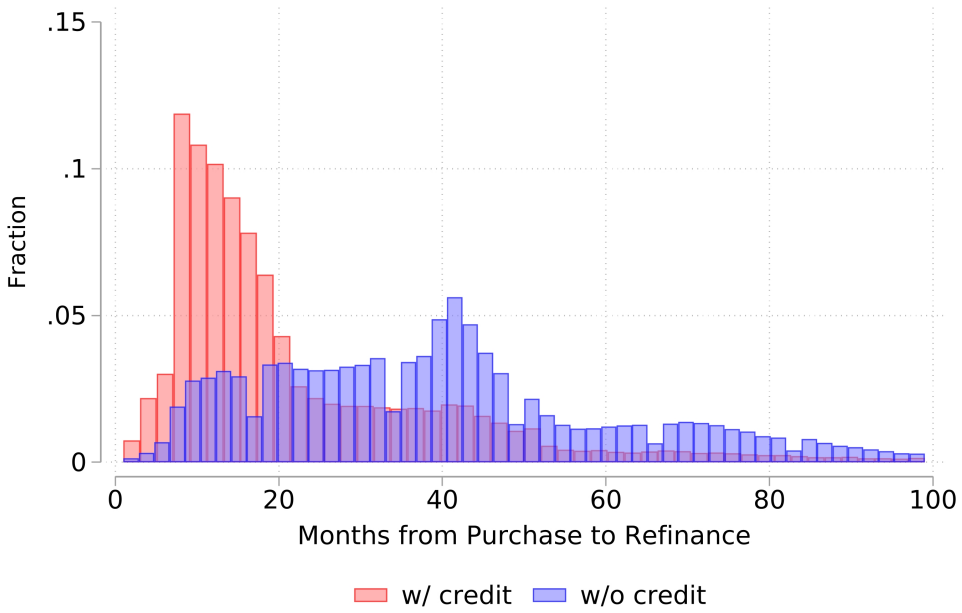
Note: This figure plots the frequency of refinance and mortgage rate change, from 2009 to 2018, for the sample of all FHA loans originated after 2009. The x-axis is time (monthly). The y-axis on the left hand side is the frequency refinances. The y-axis on the right hand side is the 30 year mortgage rate reported in FRED. The dark blue bars represent the group who did not use lender credits; the light blue bars represent the group who used lender credits.
Source: ATTOM, McDash, FRED

Figure 2.6: Average Time to Refinance by Year



Note: This figure plots the binscatter of refinance time over refinance year for FHA refinances in the matched sample. The x-axis is the year when the refinance happened. The y-axis is the months from purchase loan to refinance loan. The blue dots represent the group who did not use lender credits; the red dots represent the group who used lender credits.
Source: ATTOM, McDash.

Figure 2.7: Historgram of Time to Refinance



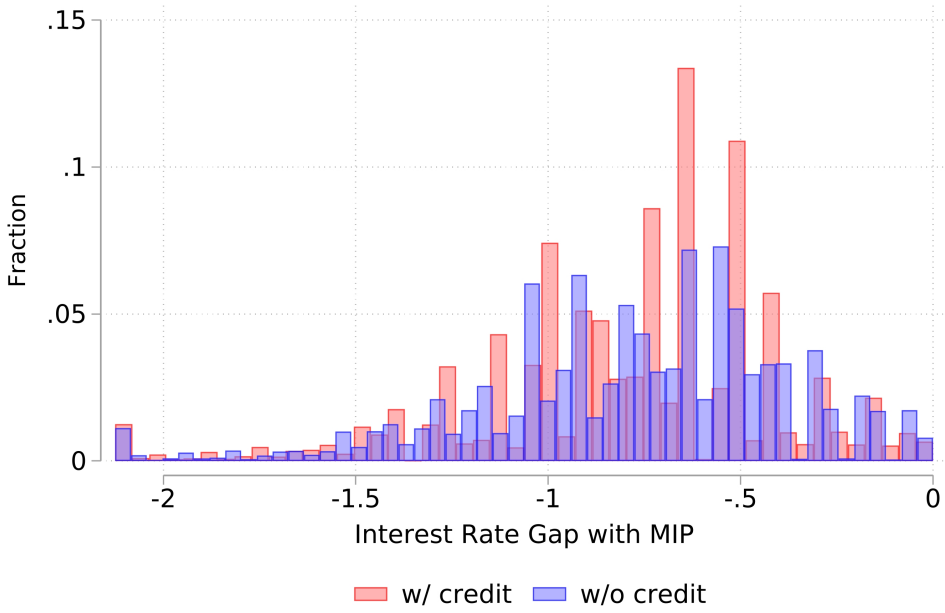
Note: This figure plots the histogram of time to refinance for FHA borrowers in the matched sample for FHA refinances in the matched sample. The x-axis is the months from purchase loan to refinance loan. The y-axis is the fraction of refinances. The blue bars represent the group who did not use lender credits; the red bars represent the group who used lender credits.
Source: ATTOM, McDash.

Figure 2.8: Histogram of Interest Rate Change from Purchase to Refinance



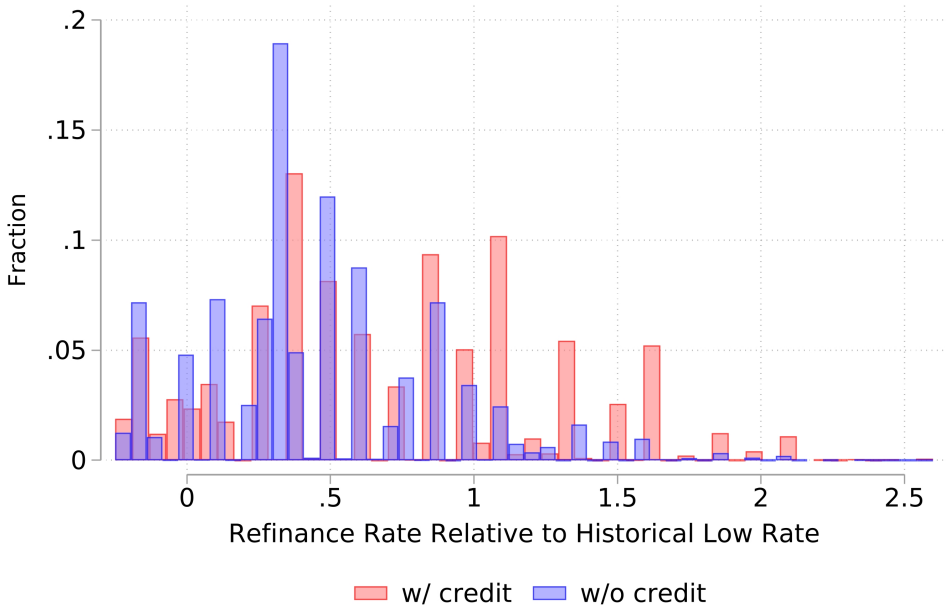
Note: This figure plots the histogram of mortgage rate difference from the purchased loan to refinance loan for FHA borrowers in the matched sample. The x-axis is the mortgage rate difference in percentage. The y-axis is the fraction of refinances. The blue bar represents the group who did not use lender credits; the red bar represents the group who used lender credits.
Source: ATTOM, McDash.

Figure 2.9: Histogram of Interest Rate Changes from Purchase to Refinance, including Changes in MIP



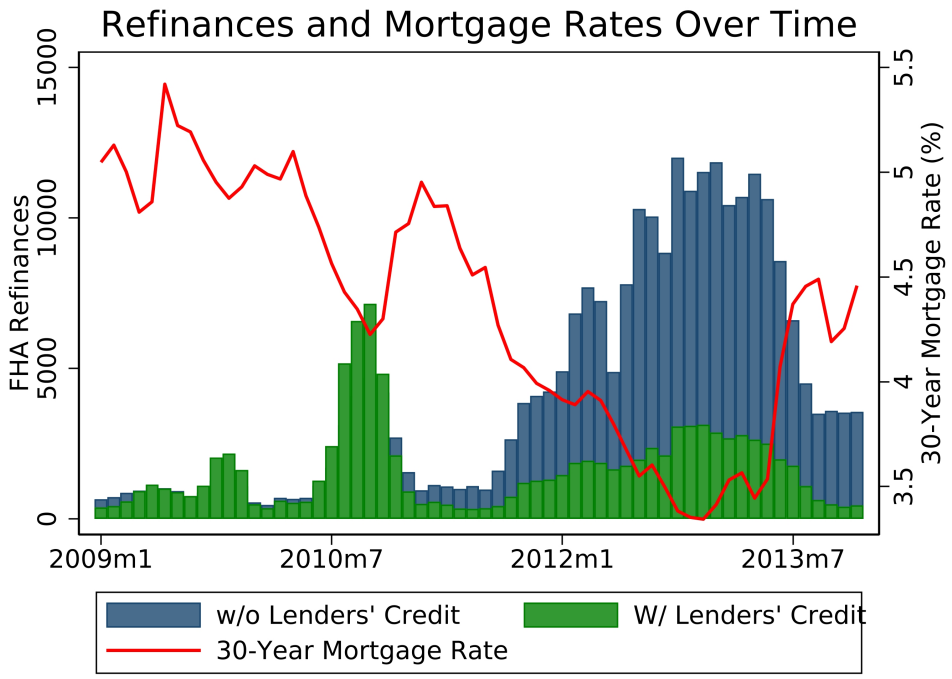
Note: This figure plots the histogram of mortgage rate difference, including changes in MIP, from the purchased loan to refinance loan for FHA borrowers in the matched sample. The x-axis is the mortgage and MIP rate difference in percentage. The y-axis is the fraction of refinances. The blue bar represents the group who did not use lender credits; the red bar represents the group who used lender credits.
Source: ATTOM, McDash.

Figure 2.10: Histogram of Interest Rate Gap from the Optimal Refinance Interest



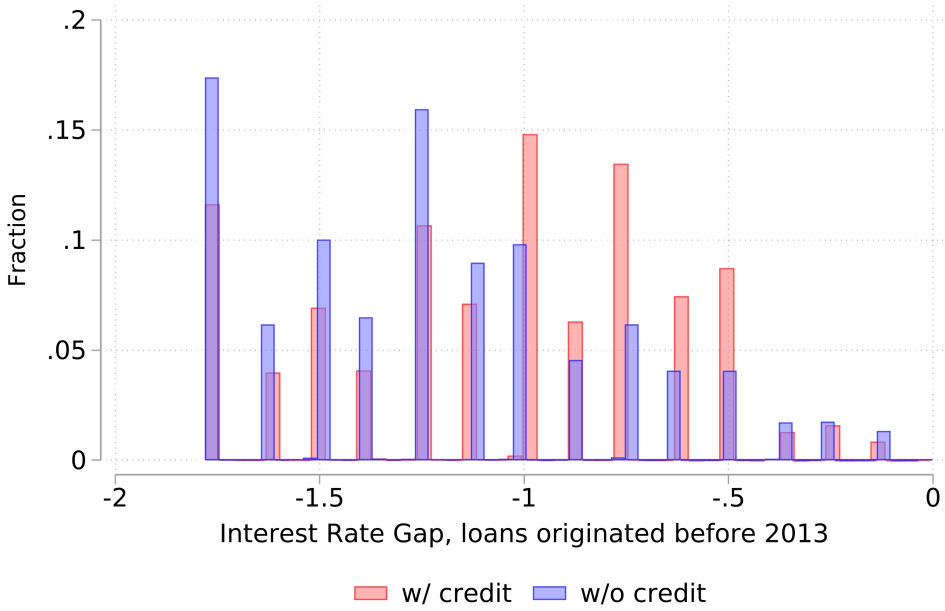
Note: This figure plots the histogram of the difference between refinance mortgage rate and the optimal refinance rate in the defined mortgage rate cycle for FHA borrowers in the matched sample. The x-axis is the difference in mortgage rate in percentage. The y-axis is the fraction of refinances. The optimal refinance interest is defined as 3.3%, the mortgage rate in November 2012, for all loans originated before November 2012; and 3.4%, the mortgage rate in November 2016, for all loans originated during November 2012 to November 2016. The blue bar represents the group who did not use lender credits; the red bar represents the group who used lender credits.
Source: ATTOM, McDash.

Figure 2.11: Frequency of Refinances and Mortgage Rate, 2009-2013



Note: This figure plot the frequency of refinance and mortgage rate change, from January 2009 to December 2013. The x-axis is time (monthly). The y-axis on the left hand side is the frequency refinances. The y-axis on the right hand side is the 30 year mortgage rate reported in FRED. The dark blue bars represent the group who did not use lender credits; the light blue bars represent the group who used lender credits.
Source: ATTOM, McDash, FRED

Figure 2.12: Histogram of Interest Rate Change for 2009-2013 Sample



Note: This figure plots the histogram of the difference between refinance mortgage rate and purchase mortgage rate from January 2009 to December 2013 for FHA borrowers in the matched sample. The x-axis is the difference in mortgage rate change in percentage. The y-axis is the fraction of refinances.
Source: ATTOM, McDash.

Tables

Table 2.1: Summary of Inaction in Refinance

Panel A: Refinanced before 2022, GSE Observations = 37,429,590

Characteristics	Mean	SD	p25	Median	p75
Interest Rate	0.043	0.009	0.038	0.043	0.049
Loan Amount	261,410	172,842	140,000	221,000	339,000
Property Value	400,259	306,994	200,000	315,000	493,000
Credit Score	754.321	47.226	725	767	791
LTV	0.720	0.661	0.598	0.750	0.800
Loan Age	44.340	31.559	19	38	63

Panel B: Did Not Refinance before 2022, GSE Observations = 31,061,091

Characteristics	Mean	SD	p25	Median	p75
Interest Rate	0.038	0.010	0.030	0.035	0.043
Loan Amount	275,081	187,830	145,000	228,000	351,000
Property Value	426,060	322,936	215,000	337,000	525,000
Credit Score	754.212	47.108	724	766	792
LTV	0.699	0.395	0.582	0.736	0.800
Loan Age	36.457	44.059	5	16	64

Panel C: Refinanced before 2022, FHA Observations = 10,497,765

Characteristics	Mean	SD	p25	Median	p75
Interest Rate	0.046	0.009	0.039	0.045	0.051
Loan Amount	195,108	103,214	124,000	172,000	242,000
Property Value	211,698	115,055	135,000	185,000	260,000
Credit Score	691.267	52.614	652	685	729
LTV	0.933	0.567	0.908	0.964	0.982
Loan Age	48.833	32.263	23	44	67

Panel D: Did Not Refinance before 2022, FHA Observations = 5,954,848

Characteristics	Mean	SD	p25	Median	p75
Interest Rate	0.041	0.010	0.034	0.040	0.048
Loan Amount	203,465	113,482	123,000	178,000	259,000
Property Value	223,769	127,074	135,000	195,000	280,000
Credit Score	678.801	48.280	645	671	707
LTV	0.923	0.521	0.892	0.963	0.982
Loan Age	49.611	51.427	6	35	91

Note: This table summarizes the main relevant variables for loans originated from 2009 to 2022, separated by their status of refinance until January 2022 for different loan types. Panels A and B show statistics for GSE mortgages that were refinanced and not refinanced before 2022, respectively. Panels C and D show statistics for FHA mortgages that were refinanced and not refinanced before 2022. Loan Age is defined as the months from origination to refinance for refinanced loans, and the months from origination to January 2022 for loans that are not refinanced.

Source: McDash

Table 2.2: Loan Characteristics and Inaction in Refinance

VARIABLES	(1) GSE	(2) FHA	(3) Jumbo
Credit Score	-0.000191***	-0.000506***	-0.000106***
	(1.99e-06)	(2.79e-06)	(8.95e-06)
LTV	-0.0344***	-0.000827***	-1.44e-05
	(0.000274)	(0.000232)	(0.000296)
Interest Rate	-3.672***	-5.068***	-5.147***
	(0.0176)	(0.0321)	(0.0598)
Property Value	-1.20e-07***	-5.28e-07***	6.11e-08***
	(3.25e-10)	(1.35e-09)	(8.91e-10)
Constant	0.862***	1.057***	0.681***
	(0.00185)	(0.00264)	(0.00755)
Observations	20,169,472	8,752,967	1,368,988
R-squared	0.415	0.334	0.449
County FE	YES	YES	YES
Quarter FE	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows OLS estimates of a linear probability model on factors correlated with no refinance. The dependent variable is a dummy variable indicating the purchase loan originated since 2009 have never been refinanced until 2022. Column (1) shows the estimation results for GSE loans; column (2) shows the estimation results for FHA loans; column (3) shows the estimation results on Jumbo Loans.
Source: McDash, author's own calculations.

Table 2.3: Summary Statistics for FHA Refinance Loans

Panel A: All FHA Refinance Loans Observations = 832,203

Variables	Mean	SD	Median
Loan Amount	216011.3	90512.8	205000
LTV	93.433	7.0120	96.500
Interest Rate	0.0425	0.0064	0.0413
Rate Spread	1.2727	0.5619	1.2200
Total Loan Cost	7376.6	2804.7	6958.8
Total Loan Cost %	3.6737	1.2589	3.4898
Points	1590.0	1327.1	1200.0
Points %	0.8669	0.6878	0.6952
Lender Credits	1348.0	1598.1	600.0
Lender Credits %	0.5901	0.6621	0.3065

Panel B: FHA Refinance Loans with LTV $>$ 96.5% Observations = 245,537

Variables	Mean	SD	Median
Loan Amount	219240.8	89801.5	205000
LTV	99.092	1.4610	99.390
Interest Rate	0.0430	0.0065	0.0425
Rate Spread	1.3759	0.5690	1.3420
Total Loan Cost	7038.3	2900.3	6515.6
Total Loan Cost %	3.4312	1.3347	3.2344
Points	1523.8	1294.1	1130.8
Points %	0.7795	0.6266	0.6138
Lender Credits	1506.4	1616.1	929.4
Lender Credits %	0.6492	0.6555	0.4349

Note: This table summarizes the characteristics of FHA refinance loans based on HMDA data. Panel A includes all FHA refinance loans, while Panel B focuses on the subset of FHA refinance loans with Loan-to-Value ratios greater than 96.5%. The table reports weighted means, standard deviations, and median values for key loan characteristics.
Source: HMDA

Table 2.4: Use of Lenders Credit and Borrower Characteristics

VARIABLES	(1) w/credit	(2) w/credit	(3) w/credit	(4) w/credit	(5) w/credit
loan amount	-1.69e-07***	-2.00e-07***	-3.88e-07***	-1.89e-07***	-3.95e-07***
	(7.15e-09)	(7.90e-09)	(7.29e-09)	(7.22e-09)	(8.07e-09)
Black		0.0762***			0.0838***
		(0.00171)			(0.00172)
Asian		-0.00531			-0.00601*
		(0.00356)			(0.00362)
Hispanic		0.0459***			0.0544***
		(0.00166)			(0.00165)
Credit Union	0.0880***				0.0875***
	(0.00499)				(0.00497)
Non Bank	0.0447***				0.00349**
	(0.00152)				(0.00154)
DTI 30-36			0.0328***		0.0277***
			(0.00190)		(0.00204)
DTI 36-40			0.0633***		0.0547***
			(0.00182)		(0.00196)
DTI 41-45			0.0928***		0.0841***
			(0.00175)		(0.00189)
DTI 46-49			0.0284***		0.0178***
			(0.00182)		(0.00197)
Age 35-44				-0.0251***	-0.0406***
				(0.00130)	(0.00140)
Age 45-54				-0.0464***	-0.0675***
				(0.00142)	(0.00154)
Age 55-64				-0.0698***	-0.0956***
				(0.00176)	(0.00194)
Age 65-74				-0.0985***	-0.134***
				(0.00273)	(0.00308)
Age ¿74				-0.138***	-0.169***
				(0.00547)	(0.00621)
Constant	0.282***	0.317***	0.263***	0.363***	0.272***
	(0.00211)	(0.00188)	(0.00210)	(0.00182)	(0.00277)
Observations	811,418	694,607	692,385	832,127	569,669
R-squared	0.039	0.044	0.058	0.041	0.082
County FE	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows OLS estimates of a linear probability model on factors correlated with FHA borrowers refinance using lenders credit. The dependent variable is a dummy variable indicating the LTV is greater than 96.5. Column (1) shows the correlation with lenders, with bank lenders as the baseline group; column (2) shows the correlation with race, with White as the baseline group; column (3) shows the correlation with debt-to-income ratio, with DTI<30 as the baseline group; column (4) shows the correlation with applicant age, with age¡35 as the baseline group. Column (5) shows a saturated model with all the variables included. *Source:* HMDA, author's own calculations.

Table 2.5: Summary Statistics

Panel A: FHA Refinance without Lender Credits Observations = 168,353

Variables	Mean	SD	p25	Median	p75
Montly Pmt. (Prepaid Loan)	1283.0	520.3	879.8	1175.4	1573.2
Montly Pmt. (Refi. Loan)	1148.0	477.3	777.3	1045.5	1411.7
Int. Rate (Prepaid Loan)	0.0506	0.00555	0.0475	0.0500	0.0550
Int. Rate (Refi. Loan)	0.0393	0.00474	0.0375	0.0388	0.0425
LTV at Origination (Prepaid Loan)	0.921	0.0963	0.897	0.962	0.982
LTV at Origination (Refi. Loan)	0.910	0.0620	0.885	0.928	0.954
FICO (Prepaid Loan)	701.6	54.45	660	697	745
FICO (Refi. Loan)	710.2	54.43	671	708	754
Prop. Value (Prepaid Loan)	246,627	119,638	162,000	220,000	300,000
Prop. Value (Refi. Loan)	239,892	115,275	159,000	215,000	290,000
Time to Refinance	38.21	24.31	21	37	48

Panel B: FHA Refinance with Lender Credits Observations = 74,396

Variables	Mean	SD	p25	Median	p75
Montly Pmt. (Prepaid Loan)	1346.9	519.4	947.0	1245.4	1646.5
Montly Pmt. (Refi. Loan)	1235.4	479.0	865.9	1145.1	1513.8
Int. Rate (Prepaid Loan)	0.0506	0.00621	0.0463	0.0500	0.0550
Int. Rate (Refi. Loan)	0.0417	0.00582	0.0375	0.0413	0.0450
LTV at Origination (Prepaid Loan)	0.953	0.0770	0.958	0.979	0.982
LTV at Origination (Refi. Loan)	0.989	0.0183	0.977	0.983	0.995
FICO (Prepaid Loan)	700.0	51.50	660	694	739
FICO (Refi. Loan)	703.5	49.55	666	698	741
Prop. Value (Prepaid Loan)	246,948	111,879	169,000	225,000	296,000
Prop. Value (Refi. Loan)	234,958	107,356	160,000	213,000	281,000
Time to Refinance	19.58	20.12	10	15	23

Note: This table summarizes the characteristics of the merged population of borrowers who purchased their property with an FHA mortgage after 2009 and refinanced their FHA mortgage to a new FHA mortage before the end of 2019. Panel A summarizes refinance loans with LTV less than 96.5%, which indicates the borrower did not use lender credits, and Panel B summarizes refinance loans with LTV greater than 96.5%, which indicates the borrower used lender credits.
Source: ATTOM, McDash, author's own calculations.

Table 2.6: Use of Lender Credits and Lender Types

	(1)	(2)	(3)
VARIABLES	use credit	use credit	use credit
Nonbank	0.0963***	0.0517***	0.0462***
	(0.00173)	(0.00168)	(0.00176)
Same Lender	0.0751***	0.0392***	0.0337***
	(0.00173)	(0.00180)	(0.00189)
FICO Score			-0.000118***
			(1.57e-05)
LTV			0.622***
			(0.00876)
Int Rate			-8.174***
			(0.168)
Prop Value			-2.10e-07***
			(9.71e-09)
Constant	0.186***	0.228***	0.201***
	(0.00157)	(0.00150)	(0.0182)
Observations	289,835	289,643	254,731
R-squared	0.015	0.152	0.180
County FE	NO	YES	YES
Year FE	NO	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows OLS estimates of a linear probability model on factors correlated with FHA borrowers refinance using lender credits. The dependent variable is a dummy variable indicating the LTV is greater than 96.5. Column (1) shows the correlation with lenders, with bank lenders as the baseline group; column (2) shows the correlation with County and Year Fixed Effect; column (3) shows the correlation with Borrower Controls. *Source:* ATTOM, McDash, author's own calculations.

Table 2.7: Refinance Mortgage Rate and the Use of Lender Credits

	(1)	(2)	(3)
VARIABLES	Rate gap	Rate gap	Rate gap
w/ Credit	0.195***	0.197***	0.204***
	(0.00202)	(0.00203)	(0.00204)
Nonbank			-0.0230***
			(0.00191)
Same Lender			0.0710***
			(0.00204)
FICO Score			-0.000296***
			(1.70e-05)
LTV			-0.747***
			(0.00961)
Int. Rate			27.83***
			(0.154)
Prop. Value			1.06e-07***
			(1.05e-08)
Constant	0.525***	0.524***	-0.0119
	(0.00106)	(0.00106)	(0.0185)
Observations	288,624	288,428	253,840
R-squared	0.031	0.052	0.184
County FE	NO	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows OLS estimates of the use of lender credits and the refinance rate gap from optimal refinance rate. The dependent variable is the difference between refinance rate and historical optimal refinance rate. Column (1) shows the correlation with lenders, with bank lenders as the baseline group; column (2) shows the correlation with County Fixed Effect; column (3) shows the correlation with Borrower Controls. *Source:* ATTOM, McDash, author's own calculations.

Chapter 3

Mortgage Rate Expectations and Refinance Choices

3.1 Introduction

The response of household financial decisions to monetary policy depends crucially on how households form expectations about future interest rates. Evidence suggests household belief and behavior are not always align with the policy goals. This paper examine the bias in interest rate expectations, explore the heterogeneity in interest rate expectation biases, and test interest rate expectation biases in mortgage refinance choices.

Standard macroeconomic models often assume that long-term rates should reflect market expectations of future short rates and these expectations should be full information rational expectations (FIRE), emerging evidence suggests professional forecasters and financial market participants may 1) have non-FIRE expectations of future short rates and 2) conflate movements in short-term and long-term rates. Therefore, it is very reasonable to believe households, who are less informed than market participants, would have the same bias or even more.

We use professional and household surveys to empirically identify expectational frictions and bias of households' interest-rate expectations. Using Blue Chip forecasts data, we show that professional forecasts of mortgage rate are not FIRE, and professional forecasts tend to overreact to information about mortgage rate changes. Using Fannie Mae National Housing Survey data, we show that ordinary households also do not show FIRE in mortgage rate expectations. But they tend to underreact to information about mortgage rate changes.

Then we combine evidence from survey with actual household financial decisions, specifically mortgage refinancing. Using Black Knight McDash mortgage servicing dataset, we test how bias in interest rate expectations are reflected in refinance choices. We use property values as a proxy for financial sophistication, allowing us to identify differential refinancing patterns consistent with our findings from survey data. The results reveal that homeowners with lower property values (who tend to exhibit underreaction bias similar to average

households) typically refinance earlier in interest rate decline cycles. In contrast, those with higher property values (who more closely resemble professional forecasters with overreaction bias) often refinance after rates have already reached their cyclical bottom.

Literature

This research contributes to the following literature: First, this paper joins the discussion of expectation biases for macroeconomic variables. There is a growing literature that seeks to identify non-FIRE expectations formation using survey data. Coibion and Gorodnichenko (2015) introduce the forecast error on forecast revision regression and document underreaction in consensus inflation forecasts. Bordalo et al. (2020) extend Coibion and Gorodnichenko (2015) evidence to the individual level forecasts and discover overreaction in individual forecasts for most macro variables. Angeletos et al. (2021) further examine the time series of forecasts and identify a delayed over-shooting pattern in the impulse responses. Other papers, such as Fuhrer (2018), Kohlhas and Walther (2021), and Farmer et al. (ming), adopt similar approaches and propose models to explain empirical belief patterns of various macrovariables. There is also a growing literature emphasizing the role of non-FIRE expectations in Treasury bond pricing. Numerous studies suggest that the presence of subjective expectations can change our interpretation of Treasury bond yields, including Piazzesi et al. (2015), Cieslak (2018), Nagel and Xu (2022), Pang (2023), and Shue et al. (2024). Our paper focuses on the mortgage rate expectations, which is an intersection of macroeconomics and asset pricing as mortgage rates are benchmarked to Treasury bond yields but are also affected by macroeconomic conditions.

Second, this paper also join the discussion of the transmission of monetary policy through the mortgage refinance channel from the perspective of expectation formation. Di Maggio et al. (2020) provide empirical evidence that the Fed MBS purchases increased refinancing activity, reduced interest payments for refinancing households, and increased aggregate consumption. Berger et al. (2021) demonstrate that the mortgage refinancing channel's effectiveness depends not just on the current level of existing mortgage rate, but also on the previous rate path. Maxted et al. (2025) extend this analysis by showing how present bias create strategic delay in refinancing decisions, slowing down monetary policy transmission. Our paper specifically investigate the role of expectation formation in monetary policy pass-through. Our results contribute to the policy discussion about the welfare effect of monetary policy transmission, by providing a better understanding of household belief formation and financial decisions. The results will also help policymakers better understand how to communicate with the public more effectively.

Finally, this paper connects to the broad literature on financial literacy, household financial decision-making, and welfare effects of monetary policy. Seminal work by Campbell (2006) demonstrate that households with lower financial sophistication are more likely to make costly household finance errors, such as failing to refinance when it would be financially beneficial. Financial products like mortgage involve a cross-subsidy from naive to sophisticated households. Lusardi and Mitchell (2011) reviewed the literature and demon-

strates that financial illiteracy is widespread in both well-developed and rapidly changing markets, and its significant impact on suboptimal financial behaviors, including mortgage choices.

The rest of the papers goes as follows: Section 3.2 describes how to identify expectation errors. Section 3.3 use mortgage refinance data to test household interest rate expectation bias. Section 3.4 concludes.

3.2 Biases in Mortgage Rate Expectations

Traditional macroeconomic and finance models often assume that agents form full-information rational expectations (FIRE). Nevertheless, non-FIRE interest rate expectations have been extensively documented in the recent literature. Cieslak (2018) shows that short-rate expectations are non-FIRE. Wang (2021), d'Arienzo (2020), and Bordalo et al. (2020) document that long-term Treasury bond yield forecasts overreact to news while forecasts of short-term yields underreact. Shue et al. (2024) argue that long-term rate expectations irrationally react to expected changes of short-term rates, which is consistent with categorical thinking and affects mortgage and firm debt behaviors. However, as the largest debt in household sector, mortgage rate expectations and its implication on mortgage decisions are not studied particularly in this literature. We investigate how mortgage rate expectations may deviate from FIRE and how this deviation varies between professional forecasters and households.

Professional forecasters' expectations

We first analyze professional forecasters' forecasts using the Blue Chip forecasts of 30-year fixed mortgage rate. We perform various tests to check whether the forecasts are FIRE or not. We use survey forecasts for 30 year mortgage rate of both the professional forecasters and households. The professional forecasts are from the Blue Chip (BC) Financial Forecasts. The BC conducts a monthly survey during the first week of every month and asks forecasters to forecast financial variables from nowcast to four quarters ahead. Since the forecasts are for a quarterly horizon, in the empirical test, we use the middle month of the survey of each quarter (February, May, August, and November).

Surveyees should use all available information to form the most accurate forecasts if the rate forecasts are FIRE. Nordhaus (1987) formally defines what constitutes an efficient forecast. An important and testable implication of this kind of forecast is that one should not be able to predict the future realized forecast error based on any information available today. Basing on this implication, Coibion and Gorodnichenko (2015) propose the following regression of forecast errors ($z_{t+h} - E_t[z_{t+h}]$) on forecast revisions ($E_t[z_{t+h}] - E_{t-1}[z_{t+h}]$), which we refer to as "FE-on-FR" regression for short, to test whether the h-period ahead forecasts of variable z are FIRE. Under FIRE, forecast revisions from the past, which are

available at the time the forecasts are made, should not correlate with future forecast errors.

$$z_{t+h} - E_t[z_{t+h}] = \alpha + \beta(E_t[z_{t+h}] - E_{t-1}[z_{t+h}]) + \epsilon_{t+h} \tag{3.1}$$

Moreover, the sign of this regression coefficient provides additional information on whether or not forecasters under-/overreact to new information. If the forecast $E_t[z_{t+h}]$ is FIRE, then the slope of regression (3.1) is zero, $\beta = 0$. When $\beta \neq 0$, the sign of β implies that agents underreact to news of z when $\beta > 0$ or overreact to news when $\beta < 0$. This is because the forecast revision reflects how agents respond to newly received information between $t-1$ and t. A positive forecast revision with $\beta > 0$ ($\beta < 0$) predicts a corresponding positive (negative) forecast error, implying the reaction is lesser (greater) than it would be in the FIRE scenario, where forecast errors are unpredictable.

We apply the FE-on-FR regression on Blue Chip consensus forecasts of the 30-year mortgage rate of different forecast horizons. Figure 3.1 plots the coefficient β and the confidence interval. We split the sample at 2000 to be consistent with our refinance analysis in the later sections, and more importantly, to address potential changes in the forecasters' expectation formation behavior. Post-2000, β coefficients for all forecast horizons except the nowcast ($h = 0$) are significantly negative. The significance and the magnitude of the negative coefficients increase across forecast horizons. These results suggest that consensus forecasts exhibit an overreaction to news behavior, although pre-2000 sample does not display significant non-FIRE evidence.

Bordalo et al. (2020) propose to also run the FE-on-FR regression with the individual forecasts to better assess the irrational expectations as the consensus regression reflects a mix of full information (FI) and rational expectation (RE) [1].

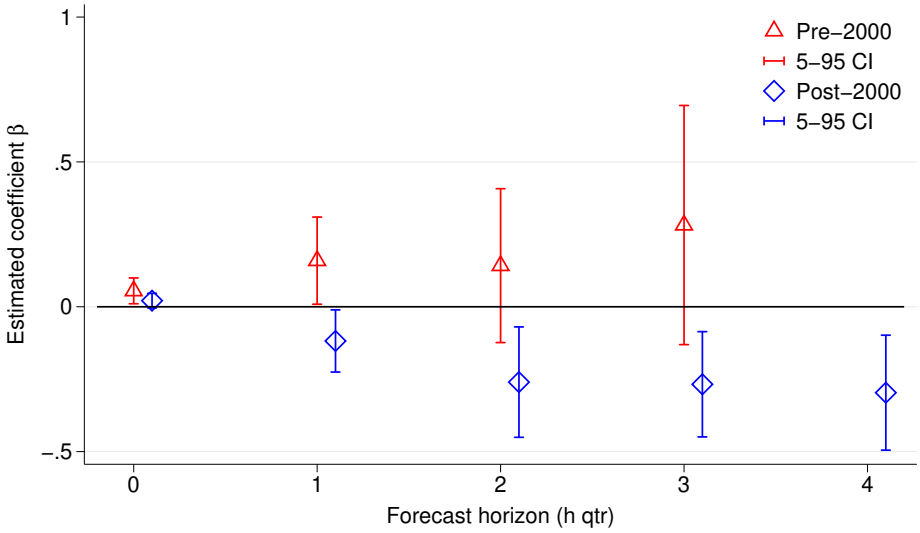
$$z_{t+h} - E^i_t[z_{t+h}] = \alpha + \beta(E^i_t[z_{t+h}] - E^i_{t-1}[z_{t+h}]) + \epsilon^i_{t+h} \tag{3.2}$$

Table 3.1 reports the results of (3.2) for the same two sample periods, pre- and post-2000. The coefficients are significantly negative and larger in magnitude than in the consensus regression for post-2000 and slightly negative for the pre-2000 period, suggesting the overreaction is coming from some individual irrational expectation formation.

The negative FE-on-FR regression coefficients along with the irrational overreaction interpretation are consistent with the findings in the literature who analyze long-term Treasury bond yield forecasts, e.g., d'Arienzo (2020) and Wang (2021). This is not surprising as long-term mortgage rate are always benchmarked with long-term Treasury yield in practice. Nevertheless, we provide direct evidence regarding mortgage rate forecasts which motivates our analysis of mortgage rate expectations and refinancing.

[1] For instance, if individual forecaster receives a noisy signal of the variable of interest, each forecaster will rationally underreact (less than one-for-one) to the noisy signal they receive as they know part of the signal is coming from the noise. However, if the noise is i.i.d across individuals, the aggregate signal will not have any noise component and thus the consensus forecast should react one-for-one. Since each individual investor reacts less, the consensus forecasts instead display underreaction.

Figure 3.1: FE-on-FR regression of Blue Chip mortgage rate consensus forecasts



Note: This figure plots the FE-on-FR regression coefficients β of regression (3.1) using the Blue Chip mortgage rate forecasts of different forecast horizons from nowcast ($h = 0$) to 4 quarters ahead. Two sample periods are reported. The red triangles and the spikes are for the sample 1982Q1:1999Q4 and the blue diamonds and the spikes are for the sample 2000Q1:2019Q4. Triangles and diamonds are for point estimates and the spikes denote 5%-95% confidence interval. HAC robust standard errors are used to calculate the confidence intervals.

FE-on-FR regression is not the only test to reject FIRE although it has the benefit of the economic interpretation of under-/overreaction. Table 3.2 further reports two additional tests using the consensus forecasts. The top panel presents the autocorrelation of the forecast errors (3.3) and the bottom panel performs the Mincer-Zarnowitz test (3.4). The first test relies on the same implication of FIRE described above that forecast errors shouldn't be predictable by any time-t information. The Mincer-Zarnowitz test is an immediate corollary of this implication that the forecasts should, on average, move one-for-one with FIRE rational forecasts. The significant constant and coefficient in regression (3.3) and the significantly different-from-one coefficient in (3.4) further suggest that professional forecasts of mortgage rate are not FIRE.

$$R_{t+h} - E_t[R_{t+h}] = \alpha + \beta(R_t - E_{t-h}[R_t]) + \varepsilon_{t+h} \tag{3.3}$$

$$R_{t+h} = \alpha + \beta E_t[R_{t+h}] + \varepsilon_{t+h} \tag{3.4}$$

Table 3.1: FE-on-FR regression of Blue Chip mortgage rate individual forecasts

Panel A: 1982Q1-1999Q4			
	$R_{t+1} - E_t^i[R_{t+1}]$	$R_{t+2} - E_t^i[R_{t+2}]$	$R_{t+3} - E_t^i[R_{t+3}]$
$E_t^i[R_{t+h}] - E_{t-1}^i[R_{t+h}]$	-0.0879	-0.128	-0.107
	(-1.17)	(-1.50)	(-1.09)
N	2768	2762	2611
FE	Yes	Yes	Yes
R^2	0.01	0.01	0.01

Panel B: 2000Q1-2019Q4			
	$R_{t+1} - E_t^i[R_{t+1}]$	$R_{t+2} - E_t^i[R_{t+2}]$	$R_{t+3} - E_t^i[R_{t+3}]$
$E_t^i[R_{t+h}] - E_{t-1}^i[R_{t+h}]$	-0.238***	-0.364***	-0.358***
	(-3.59)	(-4.73)	(-5.41)
N	3074	3064	2817
FE	Yes	Yes	Yes
R^2	0.06	0.10	0.08

Note: This Table presents the individual FE-on-FR regression coefficients β of regression (3.2) using the Blue Chip mortgage rate forecasts of different forecast horizons from 1 quarter ahead to 3 quarters ahead. Two sample periods are reported. The first three columns are for the sample 1982Q1:1999Q4 and the last three columns are for the sample 2000Q1:2019Q4. HAC robust t-stats are reported in the parentheses and the standard errors are clustered at the quarter and individual forecaster level. *, **, *** denote the estimate is significantly different from 0 at 10%, 5%, 1% significance levels, respectively.

Households expectations

Since professional forecasts are non-FIRE as we show above, it is also very likely that households, who are less informed in terms of mortgage rate dynamics, will also deviate from FIRE. To understand how mortgage decisions are affected by mortgage rate expectations, we must understand households' expectations of mortgage rates first. In this subsection, we turn to survey forecasts of households.

The household survey is from the Fannie Mae National Housing Survey (NHS). Fannie Mae initiated the NHS in 2010 to gather updated insights about individual housing-related attitudes, intentions, and financial situations, providing valuable insights on housing and mortgage market trends. Compared to other macroeconomic surveys like the Michigan Survey of Consumers, NHS data specifically target housing market and elicit questions about mortgage rate.

The main variable of interest is from Q20 of the questionnaire. Surveyees are asked the question " During the next 12 months, do you think home mortgage interest rates will go up, go down or stay the same as where they are now." Unlike the Blue Chip forecasts, the NHS forecasts only ask for the sign of the rate change in a fixed horizon, 12 months ahead. The survey results are presented in the form of the percentage of people who forecast the rate to go up and the percentage of people who forecast the rate to go down. We first construct a measure of the mortgage rate expectation as the difference between the two percentages

Table 3.2: Predictability of Blue Chip mortgage rate consensus forecast errors

	1982Q1-1999Q4		2000Q1-2019Q4	
	$R_{t+3} - E_t[R_{t+3}]$	$R_{t+4} - E_t[R_{t+4}]$	$R_{t+3} - E_t[R_{t+3}]$	$R_{t+4} - E_t[R_{t+4}]$
$R_t - E_{t-h}[R_t]$	0.0199	-0.133	-0.235***	-0.170***
	(0.12)	(-0.77)	(-4.02)	(-2.67)
Const.	-0.259	-0.416*	-0.662***	-0.830***
	(-1.51)	(-1.86)	(-9.09)	(-10.70)
N	64	65	80	80
R^2	0.00	0.02	0.07	0.04

	R_{t+3}	R_{t+4}	R_{t+3}	R_{t+4}
$E_t[R_{t+h}]$	0.810***	0.787***	0.898***	0.896***
	(14.18)	(10.41)	(19.24)	(14.77)
N	67	69	80	80
R^2	0.80	0.75	0.85	0.81
t-stat ($\neq 1$)	-3.32	-2.82	-2.18	-1.72
p val. ($\neq 1$)	0.001	0.006	0.032	0.090

Note: This Table presents the estimate of the forecast error autoregression (3.3, top panel)and the Mincer-Zarnowitz test (3.4, bottom panel) using the Blue Chip mortgage rate forecasts of forecast horizons 3 and 4 quarters ahead. Two sample periods are reported. The first two columns are for the sample 1982Q1:1999Q4 and the last two columns are for the sample 2000Q1:2019Q4. HAC robust t-stats are reported in the parentheses and *, **, *** denote the estimate is significantly different from 0 at 10%, 5%, 1% significance levels, respectively. The "t-stat($\neq 1$)" and "p val. ($\neq 1$)" rows in the bottom panel report the t-stats and p-value of testing the estimate is significantly different from 1.

(percentage of going up minus percentage of going down):

$$E_t[\text{Sign}(R_{t+12m} - R_t)] = pct_t^{up} - pct_t^{down} \tag{3.5}$$

The measure has values between -1 and 1. When all households expect rate to go up, the measure takes value of one and when all households expect rate to go down, the value is -1. Similarly, when $E_t[\text{Sign}(R_{t+12m} - R_t)] = 0$, it means half of the households expect rates to go up and half expect to go down. Figure 3.2 plots the $E_t[\text{Sign}(R_{t+12m} - R_t)]$ (blue line) along with the actual 30-year mortgage rate (red line). We also superimpose the 12-month ahead mortgage rate (red dotted line), which is what the households are forecasting.

There are two important observations from the figure. The aggregate of the households always expects rate to go up in the next 12 months as $E_t[\text{Sign}(R_{t+12m} - R_t)]$ is always positive except the last few months in 2024, even though there are a few rate cycles during this sample period. Second, although the expectations seem to be positively correlated with the realized mortgage rate, i.e., when the realized rate goes up (down), the rate expectations

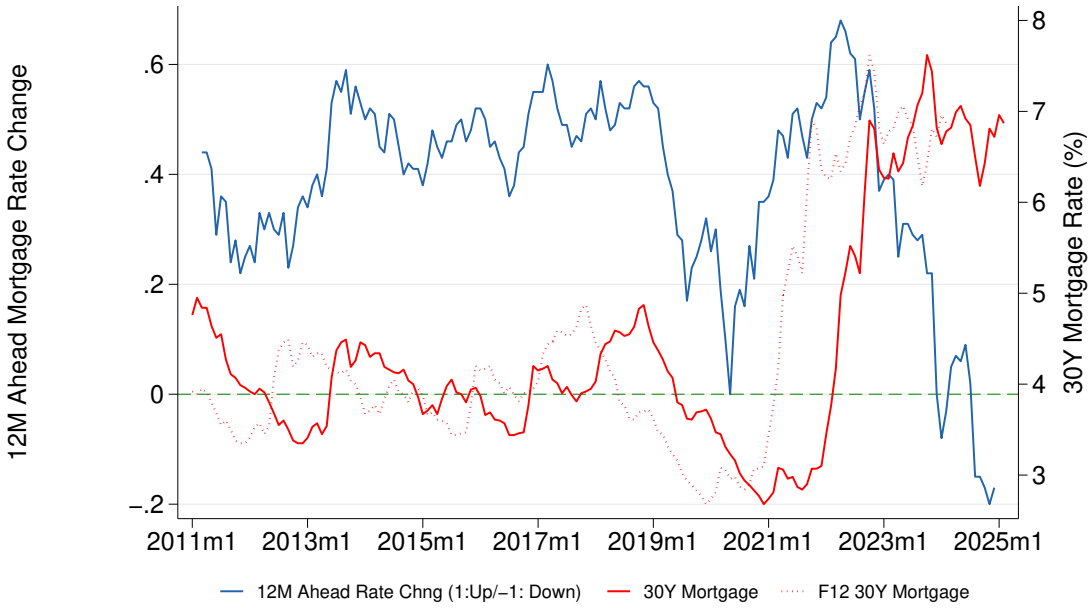


Figure 3.2: Households' 12m ahead mortgage rate forecasts

Note: This figure compares the households' 12-month forecasts of mortgage rate change from the NHS survey with the actual 30-year mortgage rate. The blue solid line plots the survey expectation of rate change in the next 12 months defined in (3.5). The red solid line plots the actual 30-year mortgage rate and the red dotted line plots the 12-month ahead 30-year mortgage rate of which the survey expectation is forecasting. The sample period is 2011m3:2024m12.

also go up (down), the correlation is not perfect. These two facts suggest that households' expectations may not be FIRE and contain information about subjective beliefs.

We consider the FE-on-FR regression again to test that households' forecasts of the mortgage rate change are non-FIRE. Table 3.3 reports the results of the test. The constants of all specifications are significantly negative, suggesting that the forecasts have positive bias, i.e., forecasters biasedly believe the rate will go up in 12 months. This is the same reading from the Figure 3.2. Moreover, unlike the professional forecasts, the coefficients of the forecast revision are positive, implying an underreaction instead of overreaction. This conclusion becomes more significant when lagged mortgage rate changes and lagged Federal funds rate changes are included as controls. These results indicate that there is a part of the subjective belief of the mortgage rate that is non-FIRE and underreacted, and is not captured by mortgage rate changes or federal funds rate changes. The two rate changes are always used by the refinance literature as either explanatory variables or controls. Thus, households' mortgage rate expectations are not redundant and provide additional information to explain households' refinance behavior.

Table 3.3: FE-on-FR regression of households' 12m ahead mortgage rate forecasts

	Sign($R_{t+12} - R_t$)-E_t[Sign]	Sign($R_{t+12} - R_t$)-E_t[Sign]	Sign($R_{t+12} - R_t$)-E_t[Sign]
E_t[Sign] $- E_{t-1}$[Sign]	2.039	2.451*	2.924**
	(1.45)	(1.85)	(2.52)
$R_t - R_{t-1}$		-0.308	0.0622
		(-0.51)	(0.11)
$R_{t-1} - R_{t-2}$			-1.179*
			(-1.81)
$FFR_t - FFR_{t-1}$		1.132	0.593
		(0.89)	(0.65)
$FFR_{t-1} - FFR_{t-2}$			2.130*
			(1.76)
Const.	-0.667***	-0.685***	-0.716***
	(-2.90)	(-3.11)	(-3.48)
N	105	105	105
R^2	0.01	0.02	0.06

Note: This Table presents the estimate of the FE-on-FR regression using the NHS 12-month mortgage rate change forecasts. The sample period is 2011m3:2019m12. The dependent variable is the difference in the sign of the actual mortgage rate change between 12 months ahead and now and the expected sign from the survey. The expected sign is defined as in (3.5). The independent variables are the forecast revision, the mortgage rate change ($R_t - R_{t-1}$) and its lag, and the Federal funds rate change ($FFR_t - FFR_{t-1}$) and its lag. HAC robust t-stats are reported in the parentheses and *, **, *** denote the estimate is significantly different from 0 at 10%, 5%, 1% significance levels, respectively.

3.3 Frictions in Mortgage Refinance

We show that households' mortgage rate expectations are not FIRE and are not perfectly explained by realized rate changes. Mortgage rate expectations affect households' refinancing decisions and mistakes. In this section, we bridge the gap between mortgage rate expectations and actual mortgage refinance choices, and show that mortgage rate expectations affect refinancing decisions. Unlike other papers who focus on home purchasing activities, we focus on mortgage refinance instead. By focusing on mortgage refinance, we make minimal assumptions on mortgage decisions. Unlike home purchasing choices which is affected by housing market and personal life events, refinance choices rely more on the monetary incentives. Mortgages can be treated as a fixed income product with embedded call options, and the option value is highly dependent on the expectation of future mortgage rates (Agarwal et al. (2013)). Intuitively, if agents overreact to news during a rate downturn, like professional forecasters, they tend to wait too long to miss the lowest rate for refinance, as they are overly convinced that the rate will go down further. Conversely, if agents underreact to news after rate goes down, like households, they may refinance too early as they believe rate will go back up soon.

Table 3.4: Summary Statistics for Refinance Loans Matched with Purchase Loan

Variables	Mean	SD	p25	Median	p75
Int. Rate (Prepaid Loan)	0.0437	0.00596	0.0400	0.0438	0.0475
Int. Rate (Refi. Loan)	0.0391	0.00589	0.0350	0.0388	0.0425
LTV at Origination (Prepaid Loan)	0.663	0.2727	0.554	0.702	0.791
LTV at Origination (Refi. Loan)	0.642	0.3940	0.544	0.673	0.753
FICO (Prepaid Loan)	756.9	48.97	730	770	792
FICO (Refi. Loan)	755.9	59.47	730	769	792
Prop. Value (Prepaid Loan)	466,337	413,840	400,000	375,000	570,000
Prop. Value (Refi. Loan)	529,018	664,701	750,000	420,000	630,000
Time to Refinance	34.33	22.19	16	29	50

Data

Our analysis of real world refinance choices is built upon the Black Knight McDash mortgage servicing dataset (McDash data), which delivers extensive mortgage performance and servicing insights for approximately 80% of mortgages across the United States. The dataset encompasses essential variables for analysis including origination date, amount borrowed, interest percentages, borrower credit score, property value, geographical location by 3-digit zip code, Loan-to-Value (LTV) measurements, and mortgage types.

There is limitation to McDash data because of anonymization, which inhibits direct tracking of refinancing relationships between new and previous loans. We merged it with ATTOM recorder information using shared variables and a statistical-learning methodology, following Bartlett et al. (2021). The ATTOM dataset supplies property transaction documentation and financial institution information from county recorder and assessor offices, along with property attributes.

Table 3.4 summarizes main mortgage characteristics (Interest Rates, LTV, Property Value, Credit Score) for the sample of GSE loans that we are able to match the refinance loan with purchase loan during 2009-2018. Table 3.5 summarizes main mortgage characteristics for the population of GSE refinance loans that were originated during 2009-2022, separated by two time periods. We would like to conduct our analysis in both of the data, because the matched sample provides more information about refinance decisions, while the population of refinance loans cover the most recent interest rate cycle and the mortgage rate have achieved an historically low level.

Mortgage rate expectations and refinancing

We next combine the households' expectations with the refinancing. Figure 3.3 plots the expectations of the mortgage rate change and the number of refinances. A puzzling observation

Table 3.5: Summary Statistics for All Refinance Loans

Variables	Mean	SD	p25	Median	p75
Panel A: Refinance Loans (January 2009 - December 2018) Observations=19,846,107					
Interest Rate	0.0430	0.0085	0.0375	0.0425	0.0475
Loan Amount ($)	215,252	208,144	120,000	181,000	272,000
Credit Score	739.5	67.1	697	754	788
Property Value ($)	335,219	419,435	167,000	255,000	400,000
LTV	0.731	0.819	0.581	0.743	0.859
Panel B: Refinance Loans (January 2019 - January 2022) Observations=14,940,874					
Interest Rate	0.0341	0.0103	0.0275	0.0313	0.0387
Loan Amount ($)	289,809	210,275	169,000	251,000	365,000
Credit Score	746.4	52.9	710	758	790
Property Value ($)	474,409	454,338	258,000	380,000	575,000
LTV	0.667	0.302	0.555	0.692	0.797

from this figure is that the expected rate change and the number of refinances negatively correlate. This observation seems to point to a counterintuitive story: When households expect future rates to go up, instead of refinancing now before the rate goes up, they choose not to refinance. When households expect future rates to go down, they decide to refinance immediately instead of waiting for a lower rate. However, this puzzle comes from the mix of two forces that affect the refinance in different directions. As shown in Figure 3.2, when the realized mortgage rate drops, the mortgage rate expectations tend to drop as well, and the refinancing is also more likely to happen.

To separate the negative effect on refinance of the actual mortgage rate change from the positive effect of the expected mortgage rate change, we regress the number of refinance on both mortgage rate expectations and mortgage rate changes. Specifically, we regress:

$$N_t - N_{t-1} = \text{const.} + \sum_{i=1}^{L_1} \beta_i E_{t-i}[\text{Sign}(R_{t-i+12m} - R_{t-i})] + \sum_{i=1}^{L_2} \gamma_i (R_{t-i} - R_{t-i-1})] + \varepsilon_t, \tag{3.6}$$

where N_t is the number of refinance in period t. Table 3.6 reports the results. We only include lags of expectations and mortgage rate changes as refinance takes time, and including contemporary terms does not alter the conclusions. We split the sample into three subperiods corresponding to three mortgage rate cycles (from peak to peak). This is because the variable of interest is the number of refinances, which is not comparable across cycles. For the first two interest rate cycles, since we have the merged mortgage refinance dataset which allows

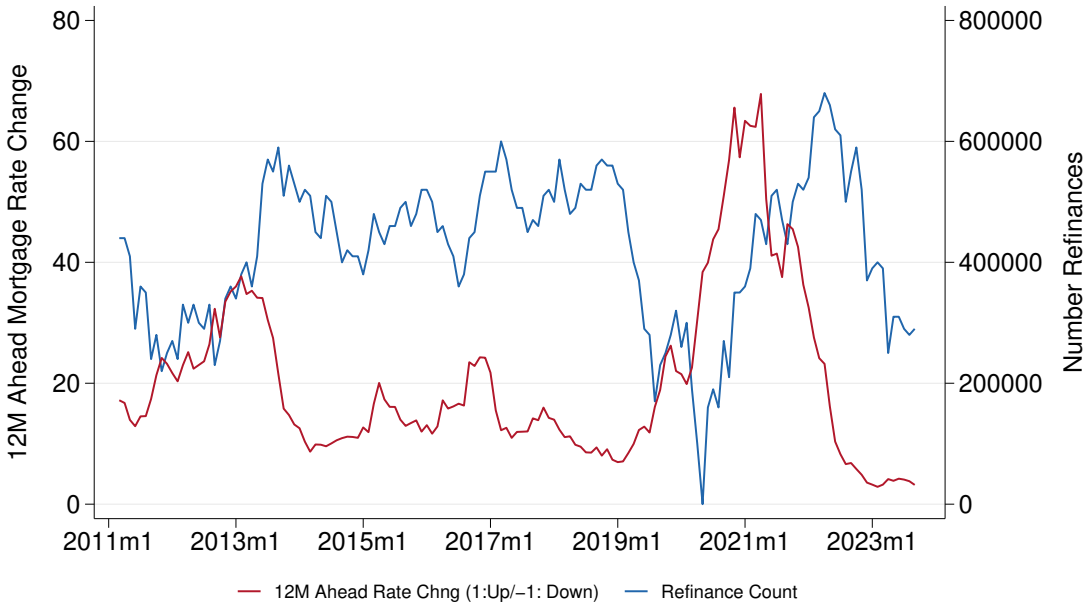


Figure 3.3: Households' 12m ahead mortgage rate forecasts and number of refinances

Note: This Figure compares the monthly survey expectation of mortgage rate change and the number of refinances. The sample period is 2011m3:2023m6. The red solid line plots the expected 12-month ahead mortgage rate changes defined in (3.5). The blue solid line superimposes the number of all refinances.

us to observe the original mortgage rate of each loan, we first drop loans that have original rates lower than the lowest available public rate within a cycle. We then drop loans that have original rates higher than the highest available public rate within a cycle. For the last sample period, since we do not observe individual rates, we consider all loans except Jumble loans.[2]

For all three samples we considered, β_i's are significantly positive and γ_i's are significantly negative, except for a few lags. The estimate is consistent with the hypothesis that an increase in the mortgage rate expectation is associated with an increase in refinance. Thus, mortgage rate expectations do play an important role in determining refinance decisions. If agents' expectations of mortgage rates are indeed non-FIRE, we should expect such bias to

[2]The reason we want to exclude the aforementioned loans is intuitive in that, first, if a loan is refinanced although it has a lower rate than the public lowest mortgage rate, it should be mainly driven by other unobserved factors which are not related to rate expectations that we are interested in. Second, if a loan's original rate is higher than the highest rate in the current cycle, the loan must be originated from the previous cycles. In this case, other behavioral or unobserved factors can confound the refinance decision, e.g., if they wait too long and miss the previous cycle's lowest rate, they may refinance too early this cycle. The last cycle in our sample period also covers the highest and the lowest mortgage rates during the last twenty years. Thus, although we do not observe the individual loan's interest rate, we can include all the loans in the sample.

Table 3.6: Number of refinance and mortgage rate forecasts

Panel A: Models without Return Controls			
	(1)	(2)	(3)
	ΔN_t 11m3:13m7	ΔN_t 13m9:16m12	ΔN_t 20m7:22m1
$E_{t-1}[\text{Sign}(R_{t+11} - R_{t-1})]$	-32.88	127.4*	190.1
	(-0.81)	(1.70)	(0.16)
$E_{t-2}[\text{Sign}(R_{t+10} - R_{t-2})]$	-146.8**	-70.25	455.7
	(-2.23)	(-1.61)	(0.35)
N	26	40	19
R^2	0.125	0.067	0.002

Panel B: Models with Return Controls			
	(4)	(5)	(6)
	ΔN_t 11m3:13m7	ΔN_t 13m9:16m12	ΔN_t 20m7:22m1
$E_{t-1}[\text{Sign}(R_{t+11} - R_{t-1})]$	172.6***	134.3**	-185.7
	(4.18)	(2.49)	(-0.25)
$E_{t-2}[\text{Sign}(R_{t+10} - R_{t-2})]$	100.3	13.86	3827.2***
	(1.56)	(0.22)	(2.61)
$R_{t-1} - R_{t-2}$	-4818.4***	-1197.8	306324.8***
	(-3.82)	(-0.75)	(4.27)
$R_{t-2} - R_{t-3}$	-19764.7***	-6682.3***	-541020.7***
	(-11.03)	(-3.19)	(-8.20)
$R_{t-3} - R_{t-4}$	3244.3***	-8358.3***	-180426.1**
	(3.19)	(-8.05)	(-2.50)
N	25	40	19
R^2	0.612	0.606	0.726

Note: This Table presents results of the number of refinance regression (3.6). Column (1) and (4) are for the interest rate cycle 2011m3:2013m7. Column (2) and (5) are for 2013m9:2016m12. Column (3) and (6) are for 2020m7:2022m1. HAC robust t-stats are reported in the parentheses and *, **, *** denote the estimate is significantly different from 0 at 10%, 5%, 1% significance levels, respectively.

lead to refinance mistakes.

Wait too long or refinance too early

Section 3.2 draws two consistent-yet-contradicting conclusions regarding the non-FIRE deviations of professional forecasters' forecasts of mortgage rates and those of households. Although they both form non-FIRE expectations of mortgage rates, professional forecasters overreact while households underreact. Unfortunately, we do not have direct observation of each group's refinancing decision. Nevertheless, we can proxy the two groups of surveyees using the observables in our refinance dataset. Specifically, we use the property value of the refinance loan as a proxy. We believe that people with higher property values are, on average, more educated in terms of the mortgage rate forecasts than people with lower property values. Thus, high property value ones are more alike professional forecasters, while low property value ones are more alike household forecasters.

Figure 3.4 plots the mean property value of each month's refinance loans. We split the data into three periods for better comparison within each period, as the property values appreciate across time. All three panels suggest that following an initial decline of the interest rate, loans that refinanced first are those with low property values. As the rate keeps dropping, the average property value of the refinanced loan goes up. This is consistent with our hypothesis that low property value refinancers alike households who underreact to mortgage rate drop and tend to refinance earlier while high property value refinancers alike professional forecasters who overreact to mortgage-rate decline and wait longer to refinance. As the red dashed line in each figure denotes the month with the lowest rate of a cycle, we can see how high-value loans are refinanced even after the lowest rate occurs. This pattern also holds within each cycle when there are few local rate cycles, such as the local dips between 2010 and 2013.

One possible confounder of Figure 3.4 is that the pattern may simply be driven by the appreciation and depreciation of the housing price due to the rate changes. To rule out this possibility, we consider relative measures of high vs. low property value refinances. For each month, we classify a refinance into the high-value group if the mortgage has a property value larger than the median property value of all mortgages originated each year. We then calculate the number of refinances of the high property value group minus the number of refinances of the low property value group, normalized by the total number of refinances of the low property value group, i.e., $\frac{N_t^{high}-N_t^{low}}{N_t^{low}}$. Figure 3.5 plots this relative measure and the mortgage rate. The conclusion remains the same that the number of low-value-mortgage refinance dominates ($\frac{N_t^{high}-N_t^{low}}{N_t^{low}} < 0$) when the rate just starts to drop. When rate keeps dropping, $\frac{N_t^{high}-N_t^{low}}{N_t^{low}} < 0$ goes up, indicating more high-value-mortgage refinances occur. Figure 3.6 plots the cumulative counterpart of Figure 3.5, where the same conclusion is still visible.

3.4 Conclusion

This paper provides new evidence on households having systematic interest rate expectation biases. Using survey data, we find that while professionals tend to overreact to interest rate changes, households typically underreact.

We then show this difference in expectational frictions lead to distinct patterns of mortgage refinancing behavior across borrowers. Using property values as a proxy, we demonstrate that borrowers with lower property values (who act more like ordinary households in their expectation formation) tend to refinance too early during declining rate environments. In contrast, borrowers with higher property values (who act more like professional forecasters) often wait too long to refinance, often refinancing after interest rates have already reached their cyclical bottom and begun to rise again. These patterns persist consistently across multiple interest rate cycles in our sample period from 2010 to 2022.

Our analysis controlling for actual interest rate movements reveals that subjective expectations about future interest rates significantly influence refinancing decisions independently of realized rates. This finding indicates that non-rational expectations are an important factor in mortgage decision-making that has been underappreciated in prior research.

These results have important implications for understanding the transmission of monetary policy through refinance channel. Interest rate changes may not affect household behavior uniformly or in ways predicted by models with rational expectations. The heterogeneity in responses across different segments of borrowers suggests that policymakers should consider the distributional effects of monetary policy actions, as different groups exhibit systematically different responses based on their expectation formation processes.

Future research could extend this work by developing structure models of household refinance decisions as a function of their interest rate expectations. Then we will be able to quantitatively measure how much bias do households have and having policy makers act accordingly.

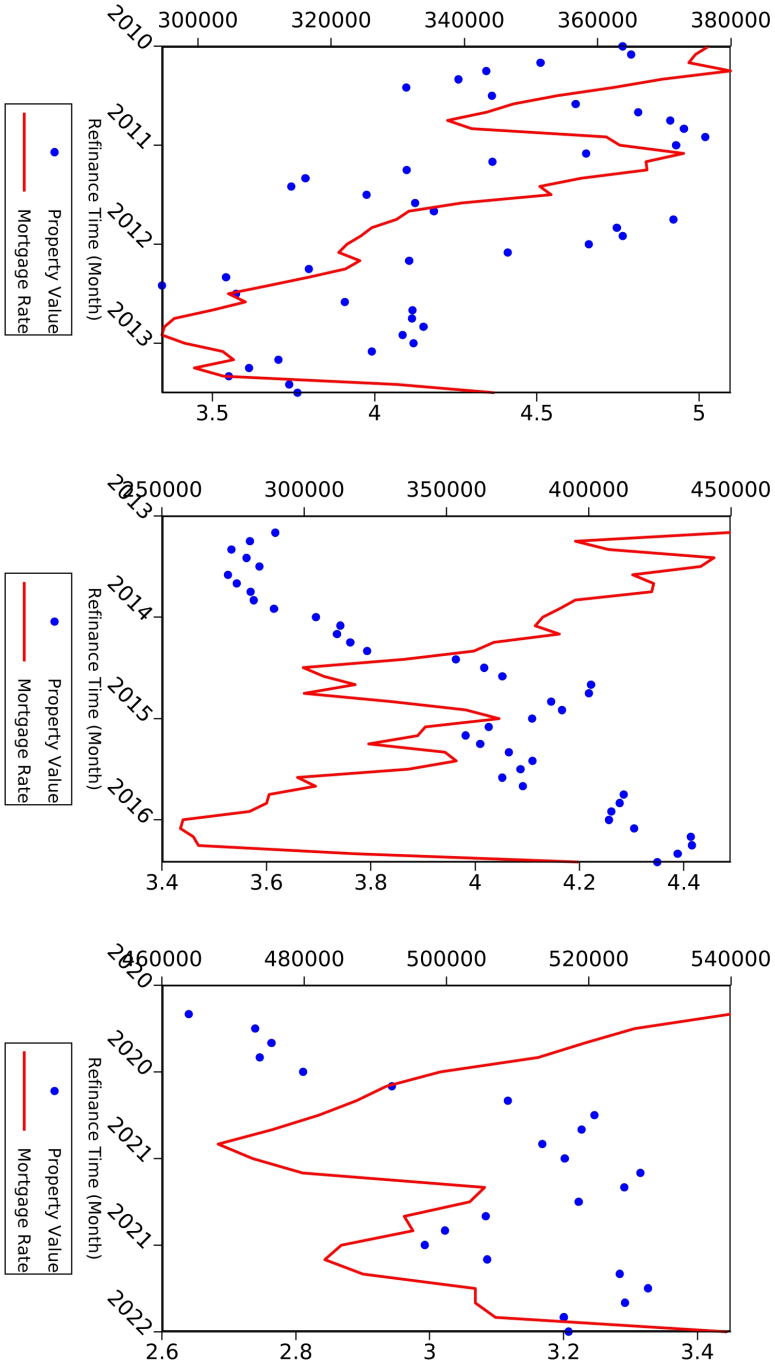


Figure 3.4: Mean Property Value by Refinance Time

Note: This figure plots the property value for conventional GSE loans and the mortgage rate using the McDash Data. The blue dots represent the mean property value of all conventional GSE loans refinanced each month. The red line shows the mortgage rate of each month. The first figure plots refinances during January 2010 to June 2013. The second figure plots refinances during September 2013 to December 2016. The third figure plots refinances during July 2020 to January 2022.

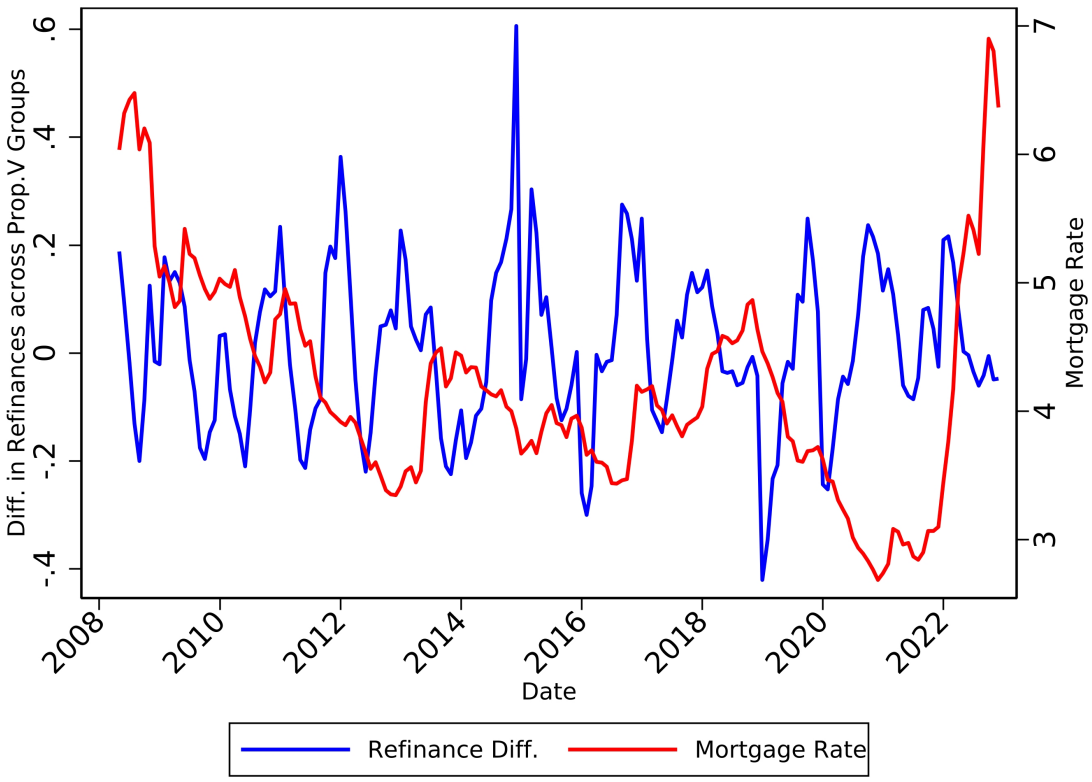


Figure 3.5: Difference of Refinance Frequency between High and Low Property Value Groups

Note: This Figure compares the monthly conventional GSE mortgage refinance frequency between groups with high and low property values. The high property value group is defined by mortgages with property value larger than the median property value of all mortgages originated each year. The blue line plots the number of refinances of the high property value group minus the number of refinances of the low property value group, normalized by the total number of refinances of the low property value group. The red solid line plots the mortgage rate.

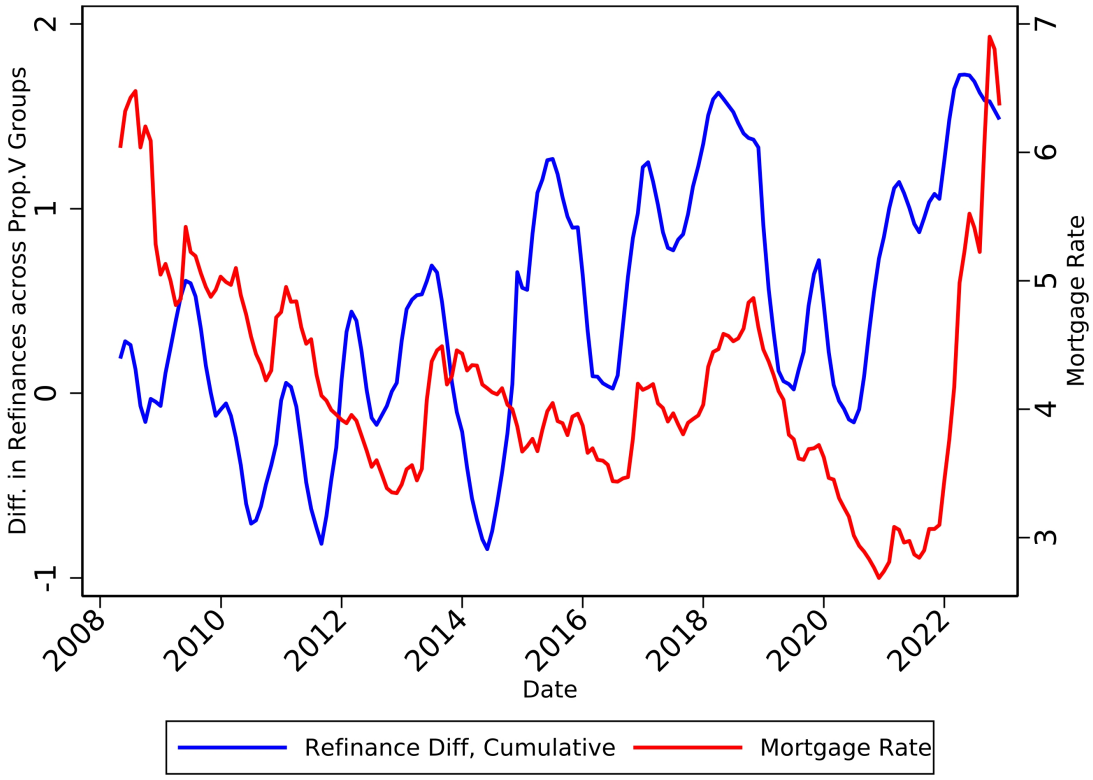


Figure 3.6: Cumulative Difference of Refinance Frequency between High and Low Property Value Groups

Note: This Figure compares the cumulative monthly conventional GSE mortgage refinance frequency between groups with high and low property values. The high property value group is defined by mortgages with property value larger than the median property value of all mortgages originated each year. The blue line plots the cumulative number of refinances of the high property value group minus the number of refinances of the low property value group, normalized my the total number of refinances of the low property value group, since the beginning of the sample. The red solid line plots the mortgage rate.

Appendix A

Appendix for Chapter 1

A.1 Additional Figures

Figure A.1: FHA Mortage Insurance Premium

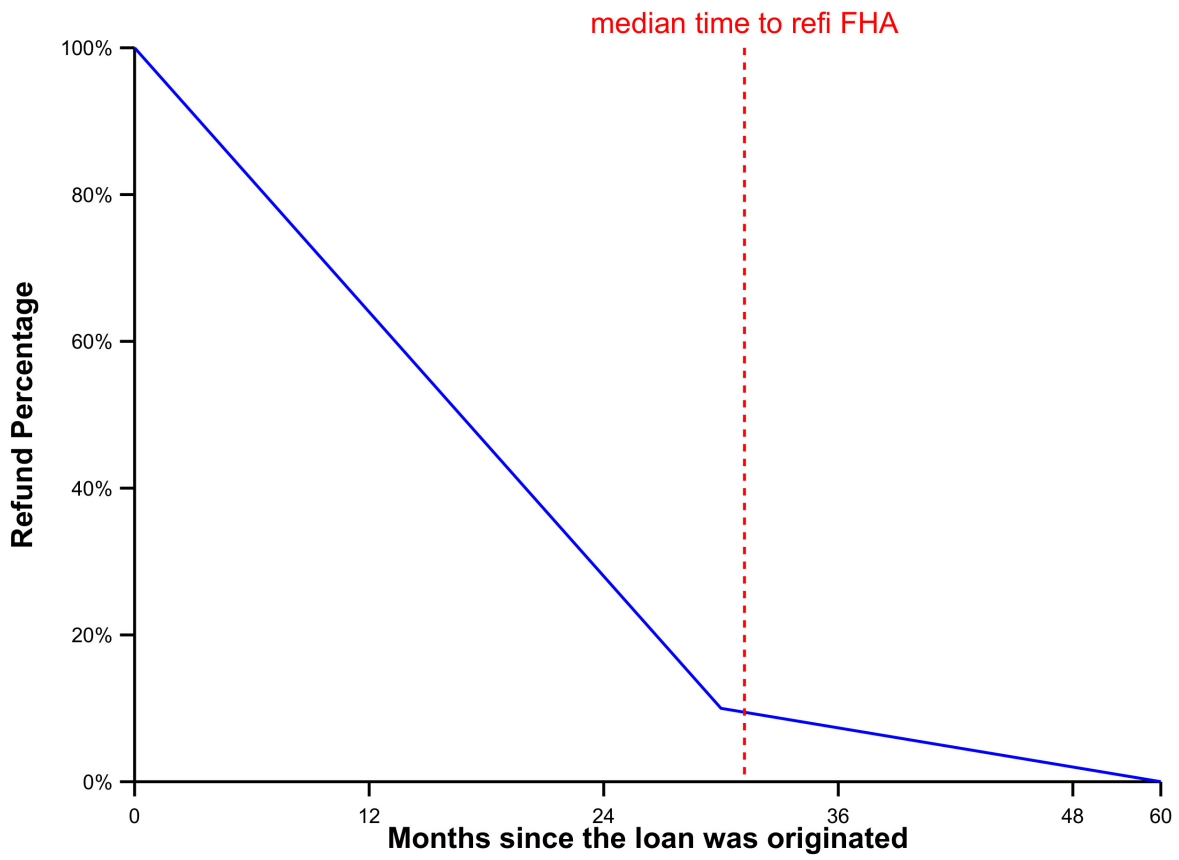
FHA premiums rose significantly in the years following the housing crash, with annual premiums rising from 50 to 135 basis points between 2008 to 2013 as FHA worked to shore up its finances. In January 2015, President Obama announced a 50 basis points cut in annual insurance premiums. In February 2023, Vice president Harris announced another 30 basis points cut to FHA insurance premiums, making FHA mortgages more attractive than GSE mortgages for the overwhelming majority of borrowers putting down less than 5%. As shown in the bottom table, a borrower putting 3.5 percent down with a FICO score less than 740 will currently find FHA financing to be more financially attractive, borrowers with FICOs of 740 and above will find GSE execution with PMI to be more attractive. This calculation reflects both the FHA MIP cut and the more favorable GSE LLPAs for LMI borrowers.

FHA MI Premiums for Typical Purchase Loan

Case number date	Upfront mortgage insurance premium (UFMIP) paid	Annual mortgage insurance premium (MIP)
1/1/2001 - 7/13/2008	150	50
7/14/2008 - 4/5/2010*	175	55
4/5/2010 - 10/3/2010	225	55
10/4/2010 - 4/17/2011	100	90
4/18/2011 - 4/8/2012	100	115
4/9/2012 - 6/10/2012	175	125
6/11/2012 - 3/31/2013[a]	175	125
4/1/2013 – 1/25/2015[b]	175	135
1/26/2015 – 3/19/2023[c]	175	85
Beginning 3/20/2023	175	55

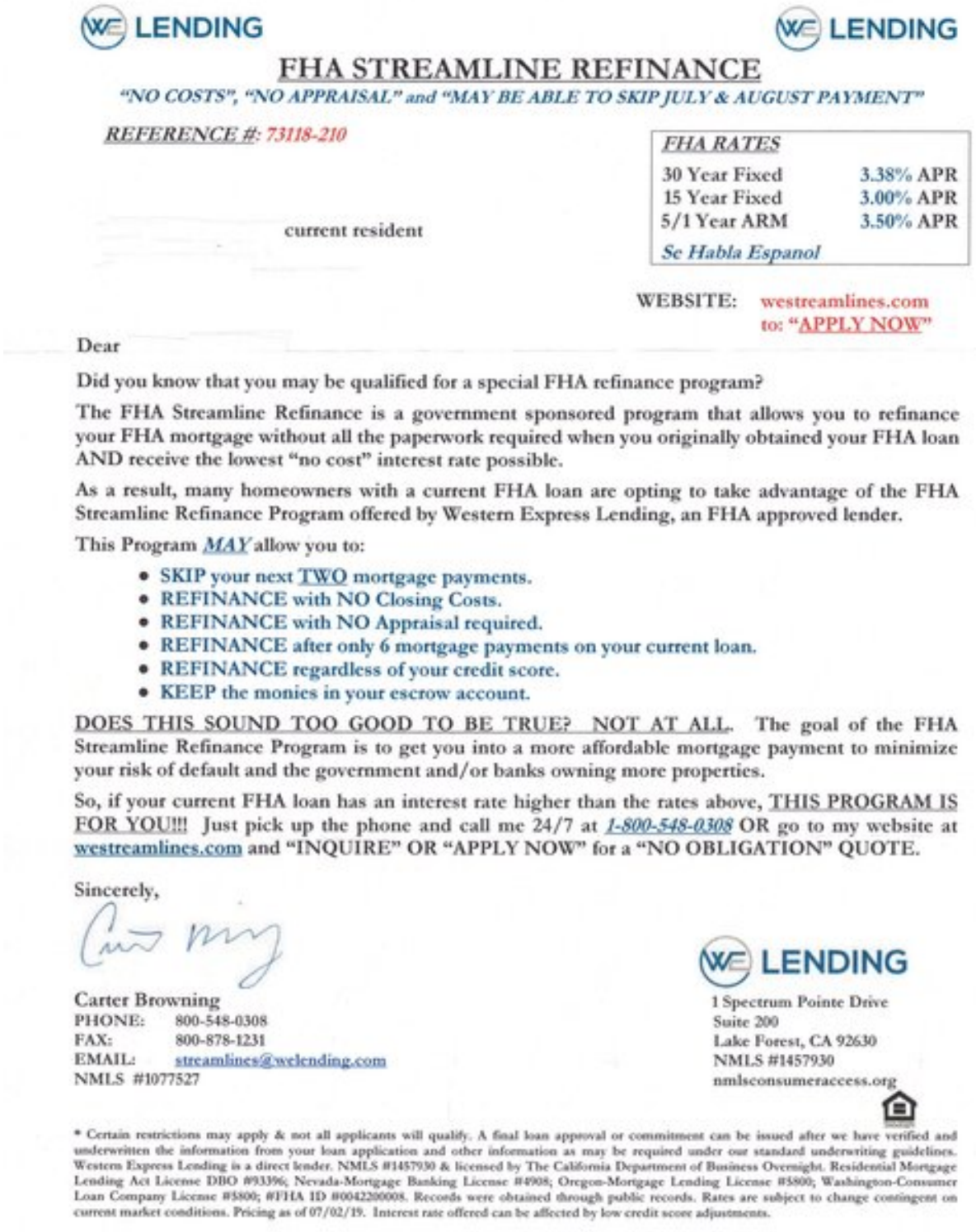
Sources: Ginnie Mae and Urban Institute.

Figure A.2: FHA Streamline Refinance Upfront MIP Refund Schedule



Note: This figure plots the UPMIP refund schedule for FHA streamline refinance program. The x-axis is the months from FHA loan origination to streamline refinance, the y-axis is percentage of UFMIP refund received by the borrower. The red vertical line is the median time (32 months) from origination to refinance in my 2010-2019 sample. More than 50% of borrowers, especially borrowers who refinance after more than 30 months, will receive less than 10% refund in UFMIP, and pay the full amount of UFMIP at the time of streamline refinance.
Source: https://www.hud.gov/program_offices/housing/comp/premiums/ufrfnd

Figure A.3: FHA Streamline Refinance Letter Advertisement



WE LENDING WE LENDING

FHA STREAMLINE REFINANCE

"NO COSTS", "NO APPRAISAL" and "MAY BE ABLE TO SKIP JULY & AUGUST PAYMENT"

REFERENCE #: 73118-210

FHA RATES	
30 Year Fixed	3.38% APR
15 Year Fixed	3.00% APR
5/1 Year ARM	3.50% APR
Se Habla Espanol	

current resident

WEBSITE: westreamlines.com
to: "APPLY NOW"

Dear

Did you know that you may be qualified for a special FHA refinance program?

The FHA Streamline Refinance is a government sponsored program that allows you to refinance your FHA mortgage without all the paperwork required when you originally obtained your FHA loan AND receive the lowest "no cost" interest rate possible.

As a result, many homeowners with a current FHA loan are opting to take advantage of the FHA Streamline Refinance Program offered by Western Express Lending, an FHA approved lender.

This Program *MAY* allow you to:

- SKIP your next TWO mortgage payments.
- REFINANCE with NO Closing Costs.
- REFINANCE with NO Appraisal required.
- REFINANCE after only 6 mortgage payments on your current loan.
- REFINANCE regardless of your credit score.
- KEEP the monies in your escrow account.

DOES THIS SOUND TOO GOOD TO BE TRUE? NOT AT ALL. The goal of the FHA Streamline Refinance Program is to get you into a more affordable mortgage payment to minimize your risk of default and the government and/or banks owning more properties.

So, if your current FHA loan has an interest rate higher than the rates above, THIS PROGRAM IS FOR YOU!!! Just pick up the phone and call me 24/7 at *1-800-548-0308* OR go to my website at westreamlines.com and "INQUIRE" OR "APPLY NOW" for a "NO OBLIGATION" QUOTE.

Sincerely,

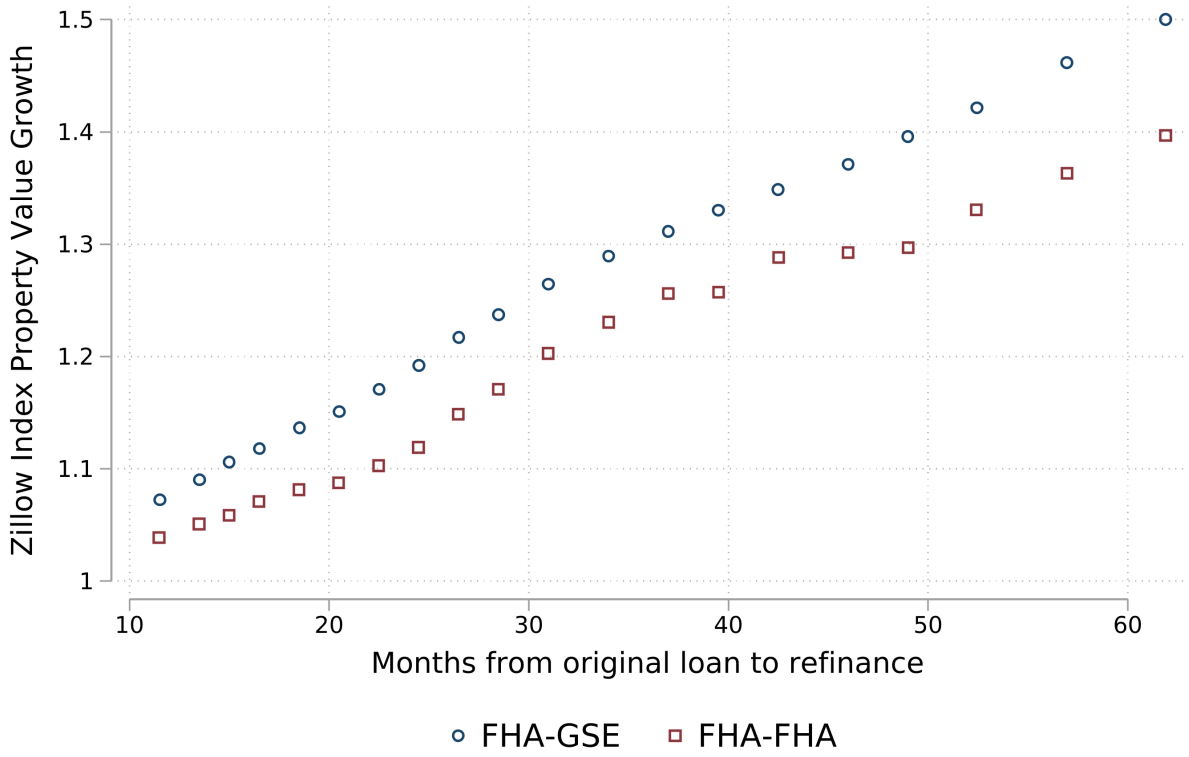
Carter Browning
PHONE: 800-548-0308
FAX: 800-878-1231
EMAIL: streamlines@welending.com
NMLS #1077527

WE LENDING
1 Spectrum Pointe Drive
Suite 200
Lake Forest, CA 92630
NMLS #1457930
nmlsconsumeraccess.org

* Certain restrictions may apply & not all applicants will qualify. A final loan approval or commitment can be issued after we have verified and underwritten the information from your loan application and other information as may be required under our standard underwriting guidelines. Western Express Lending is a direct lender. NMLS #1457930 & licensed by The California Department of Business Oversight. Residential Mortgage Lending Act License DBO #93396; Nevada-Mortgage Banking License #4908; Oregon-Mortgage Lending License #5800; Washington-Consumer Loan Company License #5800; #FHA ID #0042200008. Records were obtained through public records. Rates are subject to change contingent on current market conditions. Pricing as of 07/02/19. Interest rate offered can be affected by low credit score adjustments.

Source: https://www.theaddressers.com/mortgagemailer/fha-mortgage-direct-mail

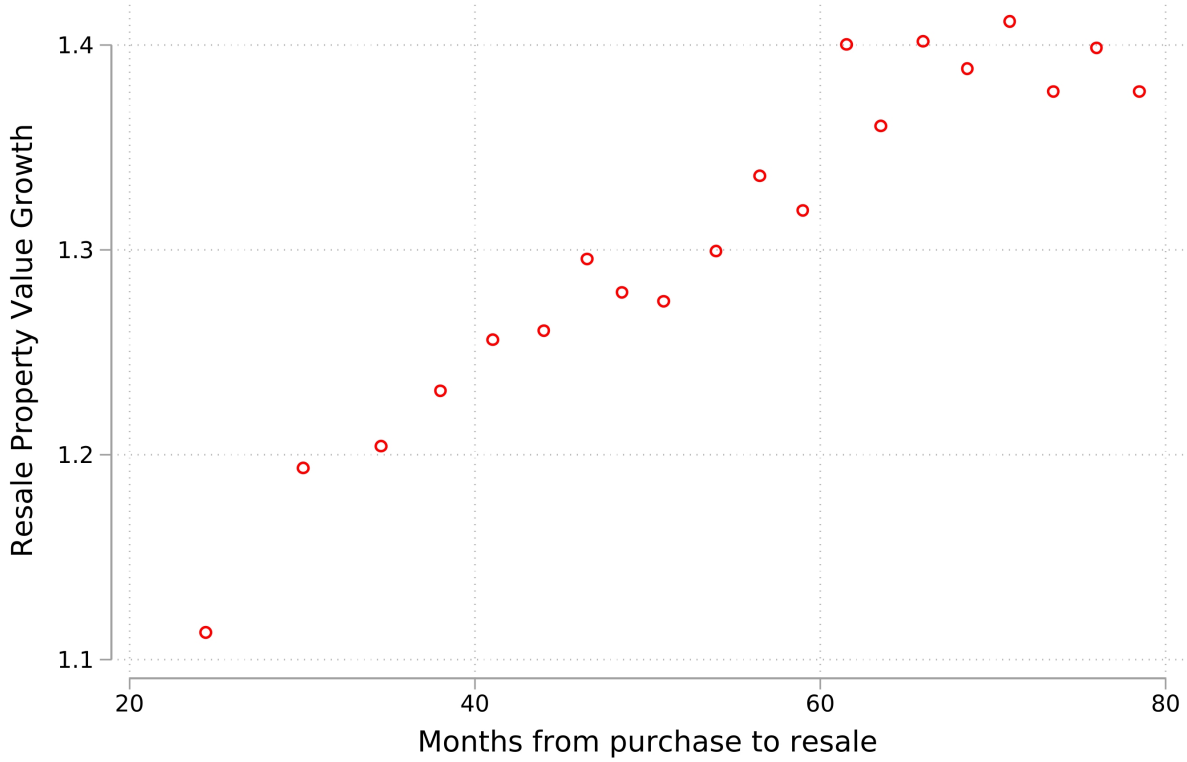
Figure A.4: Zillow Property Value Growth



Note: This figure plots the property value growth estimate using Zillow Home Value Index (ZHVI) for the sample of FHA borrowers from 2009 to 2020. The y-axis is the ZHVI of the zipcode where the property is located at the time of refinance divided by the ZHVI at the time of purchase. The x-axis is months from home purchase to refinance. The blue circle is the group where the first FHA purchase loan was refinanced to a GSE loan, the red square is the group where the first FHA purchase loan was refinance to another FHA loan.

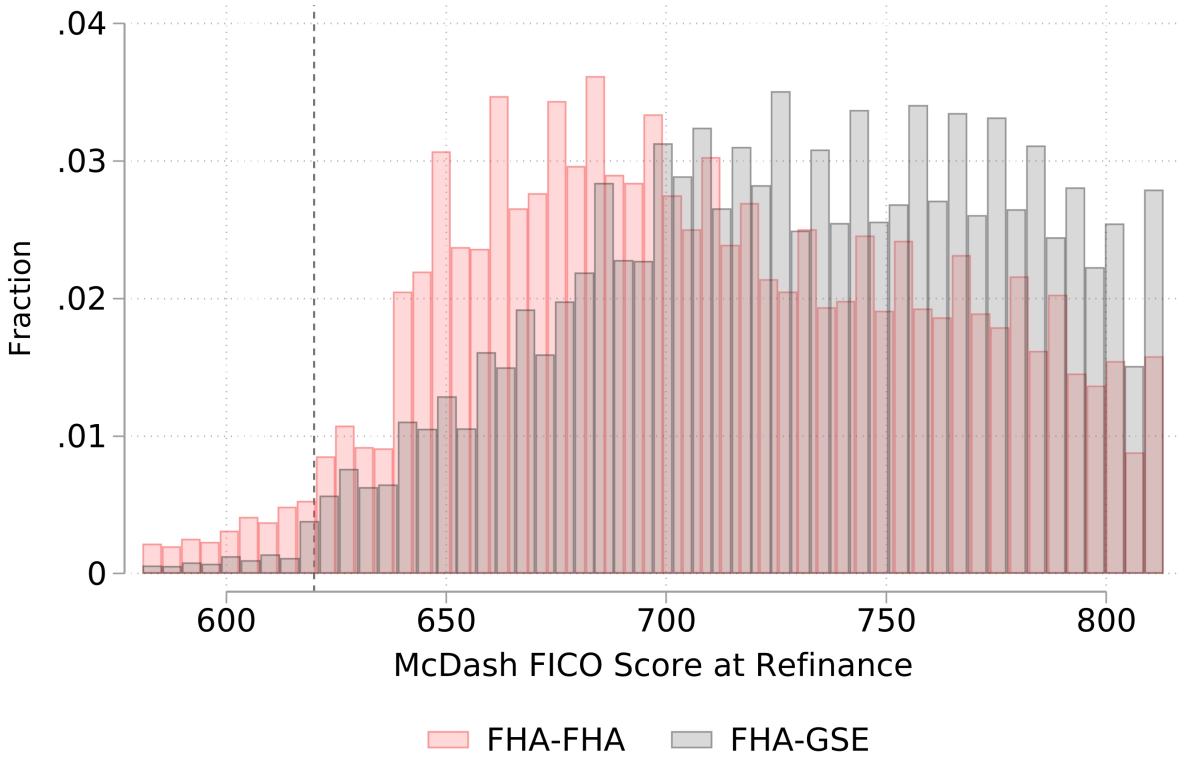
Source: Zillow, ATTOM, McDash, author's own calculations.

Figure A.5: Resale Property Value Growth



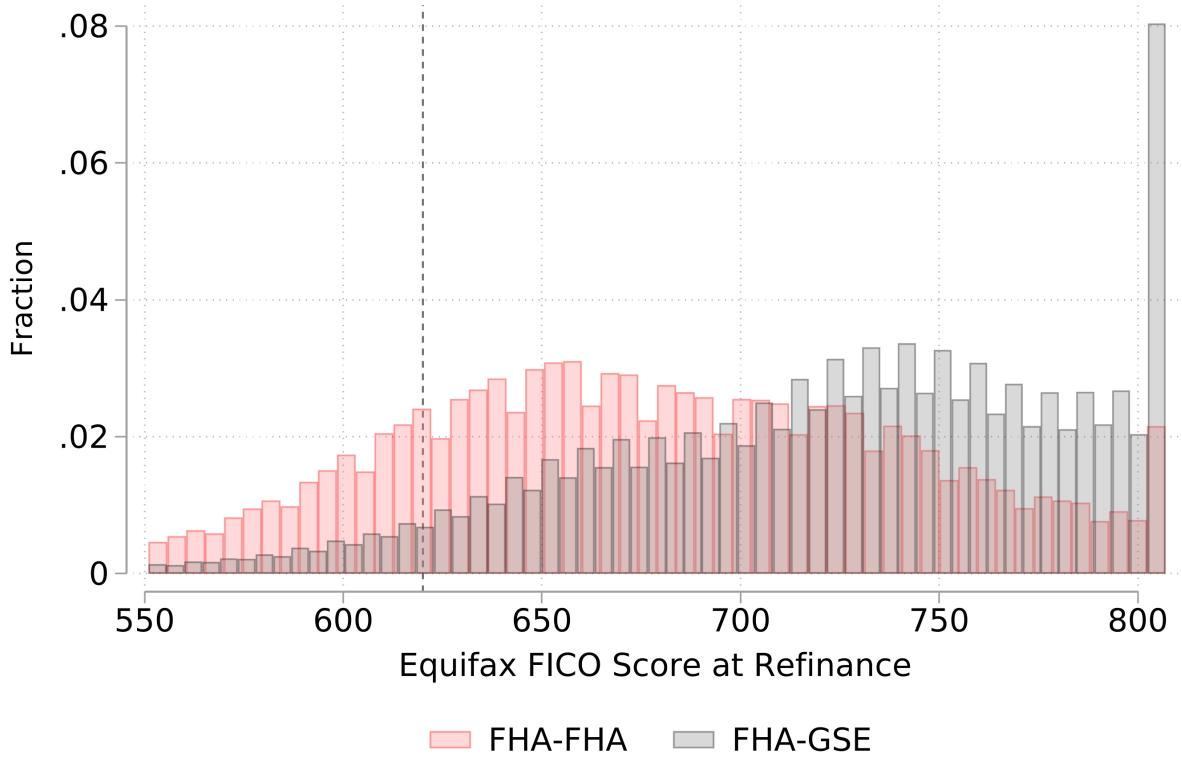
Note: This figure plots the property value growth of properties that was first purchased after 2009 with an FHA mortgage and refinanced to another FHA loan, later experienced an arm's length transfer before the end of 2020. The y-axis is the resale price divided by the purchase price, the x-axis is months from home purchase to resale.
Source: ATTOM, McDash, author's own calculations.

Figure A.6: Credit Score Distribution at Refinance



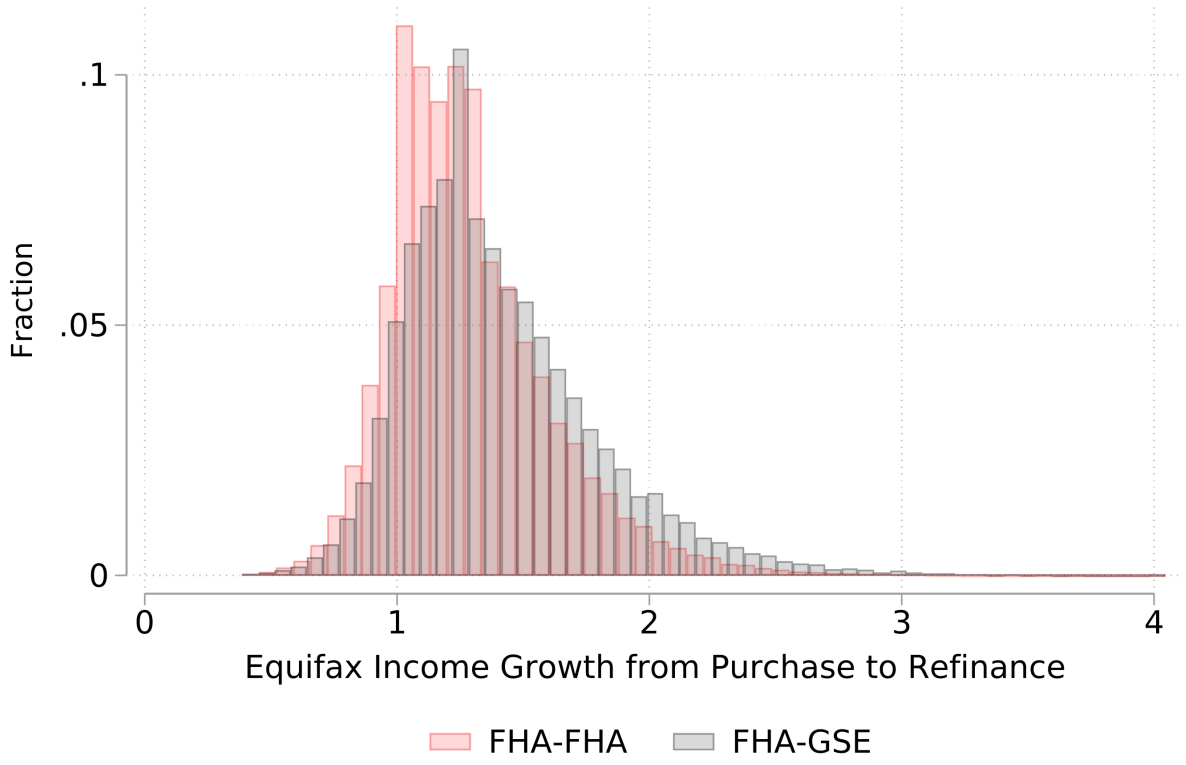
Note: This figure plots the credit score for FHA borrowers who refinanced their mortgage during the sample period in McDash. The dashed vertical line represents credit score=620 which is the typical threshold eligible for GSE mortgage. The red bar represents FHA borrowers who refinanced to another FHA loan through FHA streamline program, and the grey bar represents FHA borrowers who refinanced to a GSE loan.
Source: McDash, author's own calculations.

Figure A.7: Equifax Credit Score Distribution



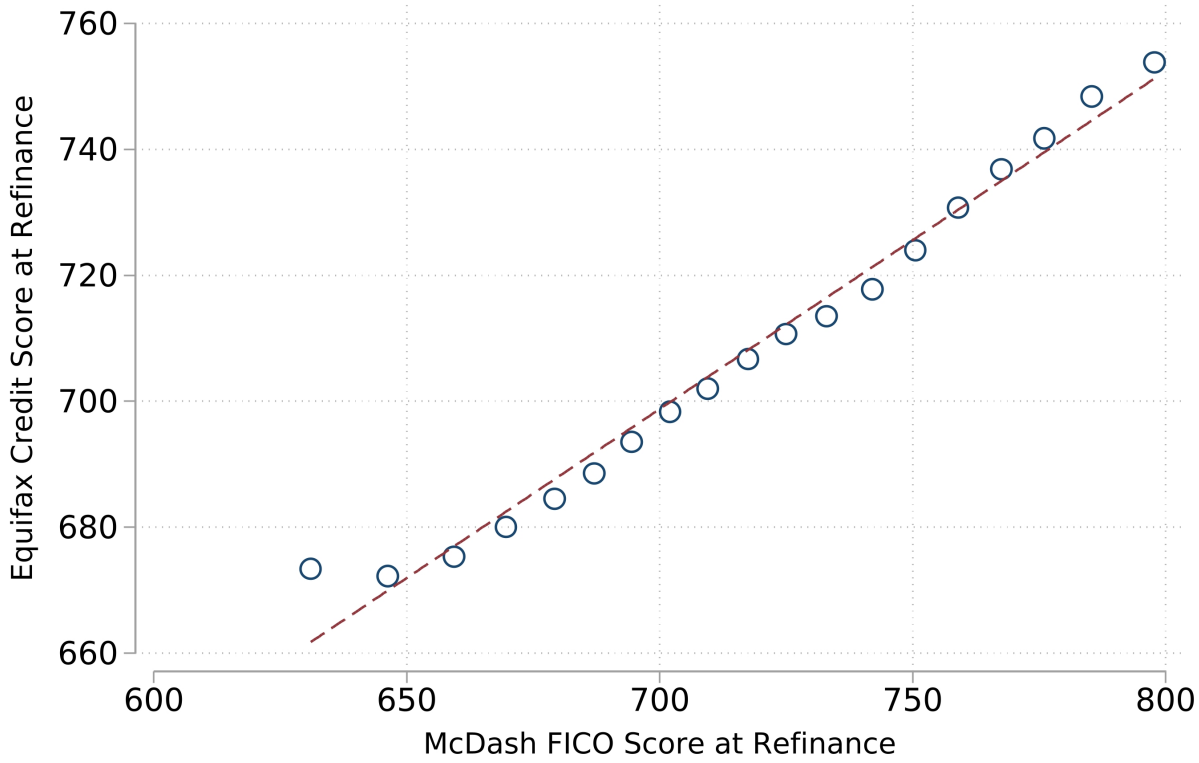
Note: This figure plots the Equifax collected credit score (vantage score 3.0) for FHA borrowers who refinanced their mortgage during the sample period. The dashed vertical line represents credit score=620 which is the typical threshold eligible for GSE mortgage. The red bar represents FHA borrowers who refinanced to another FHA loan through FHA streamline program, and the grey bar represents FHA borrowers who refinanced to a GSE loan.
Source: Equifax, McDash author's own calculations.

Figure A.8: Equifax Income Distribution



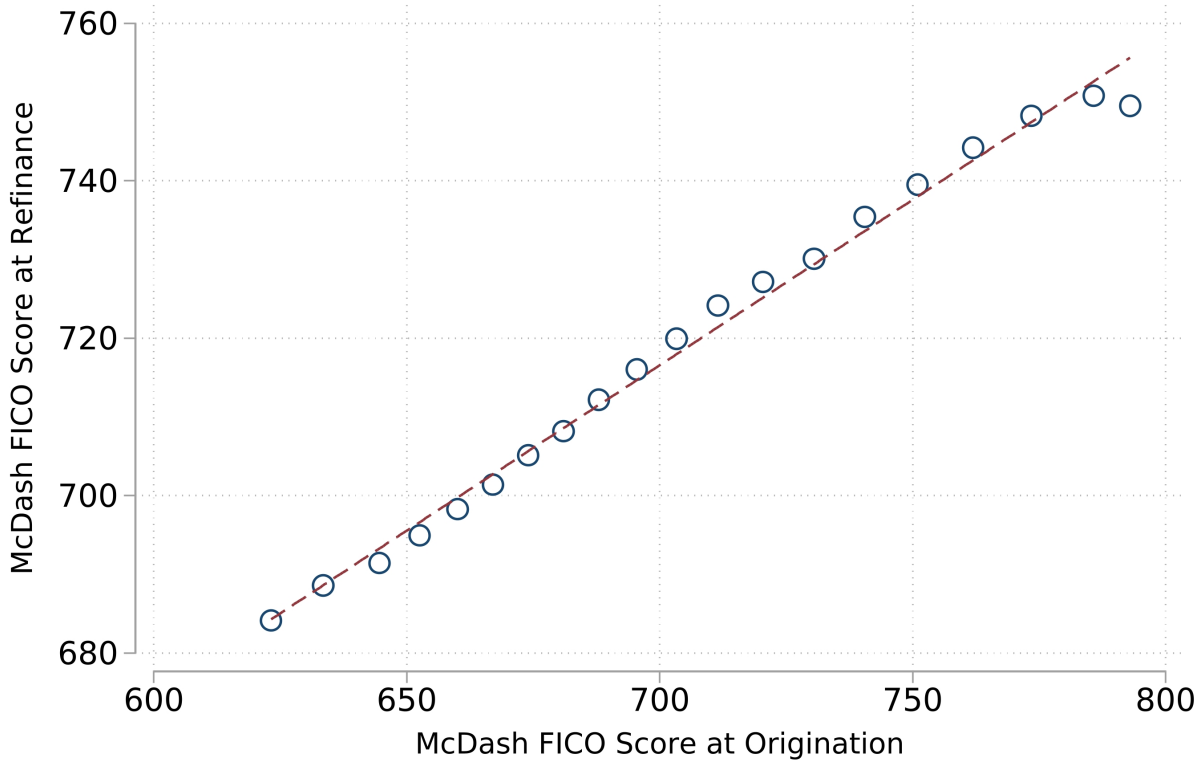
Note: This figure plots the Equifax collected borrower income change between the time of FHA loan origination and refinance. The red bar represents FHA borrowers who refinanced to another FHA loan through FHA streamline program, and the grey bar represents FHA borrowers who refinanced to a GSE loan.
Source: Equifax, McDash, author's own calculations.

Figure A.9: Equifax and McDash Credit Score Comparison



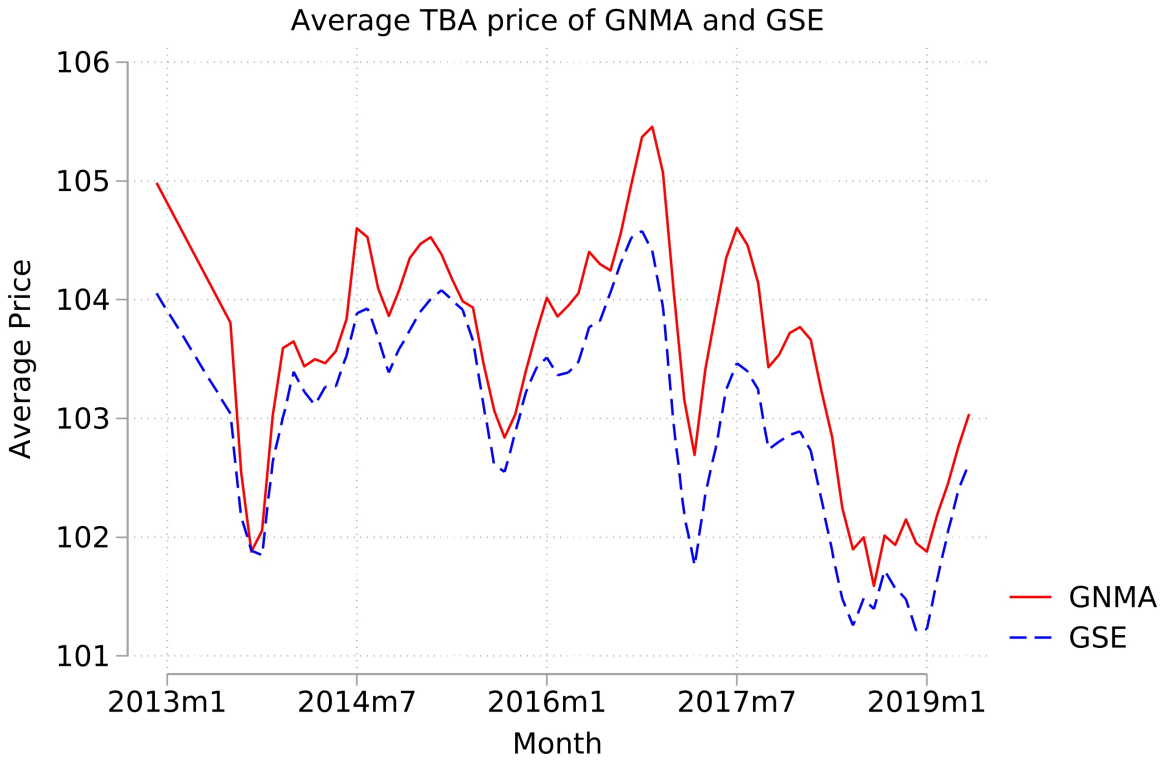
Note: This figure plots the binscatter of Equifax collected borrower credit score and McDash credit score at the time of refinance.
Source: Equifax, McDash, author's own calculations.

Figure A.10: Equifax and McDash Credit Score Comparison



Note: This figure plots the binscatter of McDash credit score at the time of origination and refinance.
Source: McDash, author's own calculations.

Figure A.11: TBA GNMA Price relative to GSE



Note: This figure plots the price of most commonly traded MBS for GNMA and GSE(FNMA and FHLMC), measured using TRACE Daily Trade Summary data from WRDS. The red line is GNMA MBS and the blue line is GSE MBS. The price are smoothed over 3 month period.
Source: TRACE.

A.2 Additional Tables

Table A.1: Summary Statistics of Merged and Dropped Sample

Merged Sample Observations = 522,561					
	Mean	SD	P25	Median	P75
Int. Rate (Prepaid Loan)	0.0476	0.00694	0.0425	0.0487	0.0525
LTV at Origination (Prepaid Loan)	0.927	0.0927	0.909	0.966	0.982
FICO (Prepaid Loan)	702.8	52.44	662	698	744
Prop. Value (Prepaid Loan)	243,865	125,559	156,000	215,000	297,000
Dropped Sample Observations = 611,734					
	Mean	SD	P25	Median	P75
Int. Rate (Prepaid Loan)	0.0454	0.00694	0.0400	0.0450	0.0500
LTV at Origination (Prepaid Loan)	0.938	0.0807	0.933	0.970	0.982
FICO (Prepaid Loan)	702.8	51.87	662	697	743
Prop. Value (Prepaid Loan)	225,630	118,023	143,000	199,000	276,000

Note: This table summarizes the loan characteristics of the merged and dropped population of borrowers who purchased their property with an FHA mortgage between 2009 and 2020. Panel A summarized the sample that successfully merged across multiple datasets for both purchase and refinance loan and end up using in the main analysis. Panel B summarized the dropped FHA loans that either the purchase loan or the refinance loan could not be merged across datasets.
Source: ATTOM, McDash.

Table A.2: R^2 of different specifications

Borrower Control	Fixed Effect Control	R^2 w/o Lender FE	R^2 w/ Lender FE	R2 Diff
Linear credit score	Year, County	0.337	0.445	0.108
Linear credit score	Year # County	0.351	0.456	0.105
LLPA Bins	Year, County	0.335	0.448	0.113
LLPA Bins	Year # County	0.355	0.160	0.105

Note: This table shows the R^2 of observables for different specifications of the linear probability model regression specified by equation 1.4. The left hand side is refinancing to GSE loan given eligible. First two rows use controls as a linear function of credit score and loan amount measures. The last two rows use credit score bins according to GSE LLPA table.

Appendix B

Appendix for Chapter 2

B.1 Omitted Proofs

Proof of *Theorem 1*

We denote the minimal cost of real interest payments under present bias β as
$W(r_0, r, \pi_0, \pi, M; \beta)$
and denote its corresponding continuation value under exponential discounting as
$V(r_0, r, \pi_0, \pi, M; \beta)$.

Step 1 *Derive HJB equation for the continuation value* $V(\cdot)$. When $\delta = i - i_0 > \Delta$,

$$\begin{aligned} E[dV] &= -(r_0 + \pi_0 - \pi)Mdt + (\rho + \lambda)Vdt - E[MdP] \\ &= -(r_0 + \pi_0 - \pi + \lambda)Mdt + (\rho + \lambda)Vdt, \end{aligned}$$

which give us

$$(\rho + \lambda)V = (r_0 + \pi_0 - \pi + \lambda)M + \frac{E[dV]}{dt}. \tag{B.1}$$

Step 2 *Establish relationship between* $W(\cdot)$ *and* $V(\cdot)$. When $\delta > \Delta$,

$$\begin{aligned} W &= E\left[\lim_{\tau \downarrow 0} \int_0^\tau (r_0 + \pi_0 - \pi + \lambda)Mdt + \beta e^{-(\rho+\lambda)\tau}(V + dV)\right] \\ &= E\left\{\lim_{\tau \downarrow 0} \beta[1 - (\rho + \lambda)\tau](V + dV)\right\} \\ &= \beta V, \end{aligned} \tag{B.2}$$

where the second equation follows from $e^{-x} = 1 - x$ for infinitesimal x.

Step 3 *Derive dynamics of* $W(\cdot)$. Combining (B.1) and (B.2), we have

$$\begin{aligned}(\rho+\lambda)W &= (r_0+\pi_0-\pi+\lambda)\beta M + \frac{E[dW]}{dt} \\ &= (r_0+\pi_0-\pi+\lambda)\beta M + \frac{1}{2}\sigma_r^2\frac{\partial^2 W}{\partial r^2} + \frac{1}{2}\sigma_\pi^2\frac{\partial^2 W}{\partial \pi^2} + \sigma_{r\pi}\frac{\partial^2 W}{\partial r \partial \pi},\end{aligned} \tag{B.3}$$

where the second equation follows from Ito formula.

Step 4 *Value matching when refinancing:*

$$W(r_0, r, \pi_0, \pi, M; \beta) = W(r, r, \pi, \pi, M; \beta) + C(M), \tag{B.4}$$

where $C(M)$ is the transaction cost of refinancing.

Step 5 *Decompose value function* W. Let the value function for mortgage without the option of refinancing be $Z(r_0, \pi_0, \pi, M; \beta)$. Therefore, the option value for refinancing is given by

$$R(r_0, r, \pi_0, \pi, M; \beta) \equiv Z(r_0, \pi_0, \pi, M; \beta) - W(r_0, r, \pi_0, \pi, M; \beta). \tag{B.5}$$

Note since refinancing is unavailable in this case, current real interest r does not affect Z.

HJB equation for $Z(r_0, \pi_0, \pi, M; \beta)$ is similar to (B.3):

$$(\rho+\lambda)Z = (r_0+\pi_0-\pi+\lambda)\beta M + \frac{E[dZ]}{dt}. \tag{B.6}$$

By "specify and verify", we obtain

$$Z = \frac{(r_0+\pi_0-\pi+\lambda)\beta M}{\rho+\lambda}. \tag{B.7}$$

The following lemma asserts that macroeconomic variables affect the option value of refinancing, $R(r_0, r, \pi_0, \pi, M; \beta)$, solely through the change in nominal interest rates, $\delta \equiv r + \pi - r_0 - \pi_0$.

Lemma 1. *For any* $\epsilon \in \mathbb{R}$,

$$R(r_0, r, \pi_0, \pi, M; \beta) = R(r_0+\epsilon, r+\epsilon, \pi_0, \pi, M; \beta) \tag{B.8}$$

$$= R(r_0, r+\epsilon, \pi_0+\epsilon, \pi, M; \beta) \tag{B.9}$$

$$= R(r_0, r, \pi_0+\epsilon, \pi+\epsilon, M; \beta). \tag{B.10}$$

Proof of Lemma 1. Denote $R(r_0, r, \pi_0, \pi, M; \beta)$ as $R(r_0, r, \pi_0, \pi)$ for short to highlight the dependence of option value on macroeconomic variables. Let the optimal refinancing threshold in state (r_0, r, π_0, π) and state $(r_0 + \epsilon, r + \epsilon, \pi_0, \pi)$ be Δ and δ, respectively. By optimality and the definitions in footnote 1, we have

$$\begin{aligned} W(r_0 + \epsilon, r + \epsilon, \pi_0, \pi) &\leq W(r_0, r, \pi_0, \pi) + \int_0^\infty D_0(t)\epsilon M dt \\ &= W(r_0, r, \pi_0, \pi) + \frac{\beta\epsilon M}{\rho + \lambda}, \qquad \text{(B.11)} \\ W(r_0, r, \pi_0, \pi) &\leq W(r_0 + \epsilon, r + \epsilon, \pi_0, \pi) - \int_0^\infty D_0(t)\epsilon M dt \\ &= W(r_0 + \epsilon, r + \epsilon, \pi_0, \pi) - \frac{\beta\epsilon M}{\rho + \lambda} \qquad \text{(B.12)} \end{aligned}$$

where (B.11) follows from the fact that household in state $(r_0+\epsilon, r+\epsilon, \pi_0, \pi)$ can do (weakly) better than refinancing at Δ by optimality, and (B.12) follows from the fact that agent in state (r_0, r, π_0, π) can do (weakly) better than refinancing δ by optimality. Combining (B.11) and (B.12), we have

$$W(r_0, r, \pi_0, \pi) = W(r_0 + \epsilon, r + \epsilon, \pi_0, \pi) - \frac{\beta\epsilon M}{\rho + \lambda}. \qquad \text{(B.13)}$$

By (B.5), (B.7) and (B.13), we have

$$R(r_0, r, \pi_0, \pi, M; \beta) = R(r_0 + \epsilon, r + \epsilon, \pi_0, \pi, M; \beta),$$

as in(B.8).

Similarly, by optimality we have

$$W(r_0, r + \epsilon, \pi_0 + \epsilon, \pi) \leq W(r_0, r, \pi_0, \pi) + \int_0^\infty D_0(t)\epsilon M dt = W(r_0, r, \pi_0, \pi) + \frac{\beta\epsilon M}{\rho + \lambda}, \qquad \text{(B.14)}$$

$$W(r_0, r, \pi_0, \pi) \leq W(r_0, r + \epsilon, \pi_0 + \epsilon, \pi) - \int_0^\infty D_0(t)\epsilon M dt = W(r_0, r + \epsilon, \pi_0 + \epsilon, \pi) - \frac{\beta\epsilon M}{\rho + \lambda}, \qquad \text{(B.15)}$$

$$W(r_0, r, \pi_0 + \epsilon, \pi + \epsilon) \leq W(r_0, r, \pi_0, \pi) + \int_0^\infty D_0(t)0 dt = W(r_0, r, \pi_0, \pi), \qquad \text{(B.16)}$$

$$W(r_0, r, \pi_0, \pi) \leq W(r_0, r, \pi_0 + \epsilon, \pi + \epsilon) - \int_0^\infty D_0(t)0 dt = W(r_0, r + \epsilon, \pi_0 + \epsilon, \pi). \qquad \text{(B.17)}$$

(B.14) and (B.15) give us $W(r_0, r, \pi_0, \pi) = W(r_0, r + \epsilon, \pi_0 + \epsilon, \pi) - \beta\epsilon M/(\rho + \lambda)$ and thus we can obtain (B.9). Likewise, (B.16) and (B.17) give us $W(r_0, r, \pi_0, \pi) = W(r_0, r, \pi_0 + \epsilon, \pi + \epsilon)$ and thus we can obtain (B.10). □

Lemma 1 implies that the only variation in macroeconomics that matters for refinancing is the nominal interest rate change. To see this, consider two states (r_0, r, π_0, π) and (r_0', r', π_0', π') which share the same nominal interest rate change $\delta = r + \pi - r_0 - \pi_0 = r' + \pi' - r_0' - \pi_0'$. By Lemma 1, we have

$$\begin{aligned} R(r_0', r', \pi_0', \pi') &= R(r_0, r' + r_0 - r_0', \pi_0', \pi') \\ &= R(r_0, r, \pi_0' + r - r' - r_0 + r_0', \pi') \\ &= R(r_0, r, \pi_0, \pi' + \pi_0 - \pi_0' - r + r' + r_0 - r_0') \\ &= R(r_0, r, \pi_0, \pi) \end{aligned}$$

where the last equation follows from the assumption that $r + \pi - r_0 - \pi_0 = r' + \pi' - r_0' - \pi_0'$. Therefore, we can rewrite $R(r_0, r, \pi_0, \pi, M; \beta)$ as $R(\delta, M; \beta)$ where $\delta = r + \pi - r_0 - \pi_0$, and decompose W as

$$\begin{aligned} W(r_0, r, \pi_0, \pi, M; \beta) &= Z(r_0, r, \pi_0, \pi, M; \beta) - R(\Delta, M; \beta) \\ &= \frac{(r_0 + \pi_0 - \pi + \lambda)\beta M}{\rho + \lambda} - R(\Delta, M; \beta). \end{aligned} \tag{B.18}$$

Step 6 *Simplify differential equation for W.* In what follows, we skip M and β as a determinant of the option value R and denote $R(\delta)$ for short. By (B.3) and (B.18), we have

$$\begin{aligned} (\rho + \lambda)W &= (r_0 + \pi_0 - \pi + \lambda)\beta M - \frac{1}{2}\sigma_r^2 R(\delta) - \frac{1}{2}\sigma_\pi^2 R''(\delta) - \sigma_{r\pi} R''(\delta) \\ &= (r_0 + \pi_0 - \pi + \lambda)\beta M - \frac{1}{2}\sigma^2 R''(\delta). \end{aligned} \tag{B.19}$$

By (B.18) and (B.19), we have the following second-order ordinary differential equation:

$$(\rho + \lambda)R(\delta) = \frac{1}{2}\sigma^2 R''(\delta). \tag{B.20}$$

Step 7 *Boundary conditions.*

$$\lim_{\delta \to \infty} R(\delta) = 0 \quad \text{[Limit Boundary]}, \tag{B.21}$$

$$R(\Delta) = R(0) - C(M) - \tfrac{\beta \Delta M}{\rho + \lambda} \quad \text{[Value Matching]}, \tag{B.22}$$

$$R'(\Delta) = -\tfrac{\beta M}{\rho + \lambda} \quad \text{[Smooth Pasting]}. \tag{B.23}$$

The *Limit Boundary* (B.21) results from the idea that if the current interest rate is arbitrarily larger than the originally contracted interest rate, then there is no refinance option value. The *Value Matching* (B.22) follows from (B.4). A shortcut to see the *Smooth Pasting* (B.23) is to differentiate and equate both sides of (B.22) with respect to Δ.

Step 8 *Solve for* Δ *using* (B.20), (B.21), (B.22) *and* (B.23). By (B.20) and (B.21), we have $R(\delta) = Ke^{-\psi\delta}$ where $K > 0$ and ψ is the positive root[1] for

$$\frac{\sigma^2}{2}y^2 - (\rho + \lambda) = 0.$$

Next by (B.23), $K = \frac{\beta M}{\psi(\rho+\lambda)}e^{\psi\Delta}$. And then by (B.22) we have

$$e^{\psi\Delta} - \psi\Delta = 1 + \psi(\rho + \lambda)\frac{C(M)}{\beta M}. \tag{B.24}$$

Solve for (B.24) and we get

$$\Delta = -\frac{1}{\psi}[\phi + W_0(-e^{-\phi})] \tag{B.25}$$

where $\phi = 1 + \psi(\rho + \lambda)C(M)/(\beta M)$ and $W_0(\cdot)$ is the principal branch of the Lambert W-function[2].

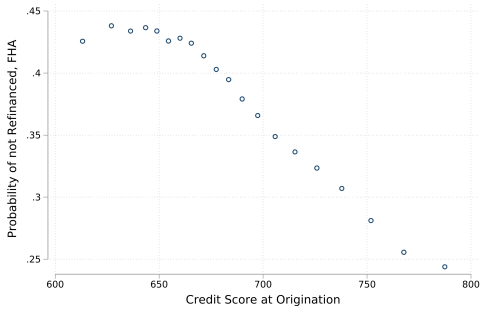
[1] A unique positive root exists for this quadratic function since $y_1 y_2 = -\frac{2(\rho+\lambda)}{\sigma^2} < 0$. We take this positive root as ψ due to the *Limit Boundary* (B.21).

[2] The principal branch of the Lambert W-function is the inverse function of $z = f(w) = we^w, w \in [-1, \infty)$.

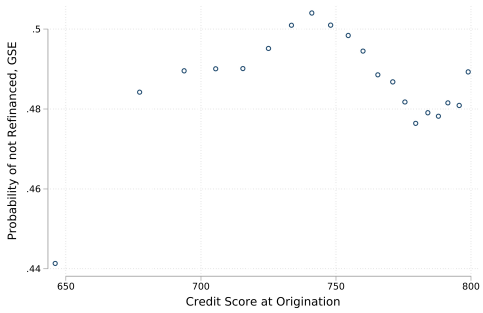
B.2 Additional Figures

Figure B.1: Inaction in Refinance and Credit Score

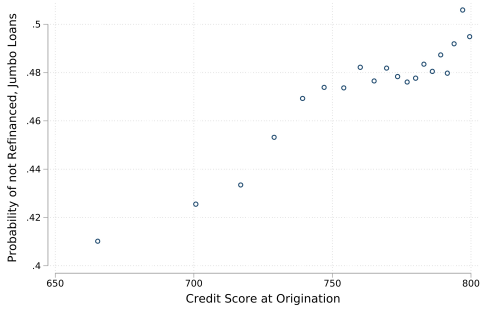
Panel A: FHA



Panel B: GSE



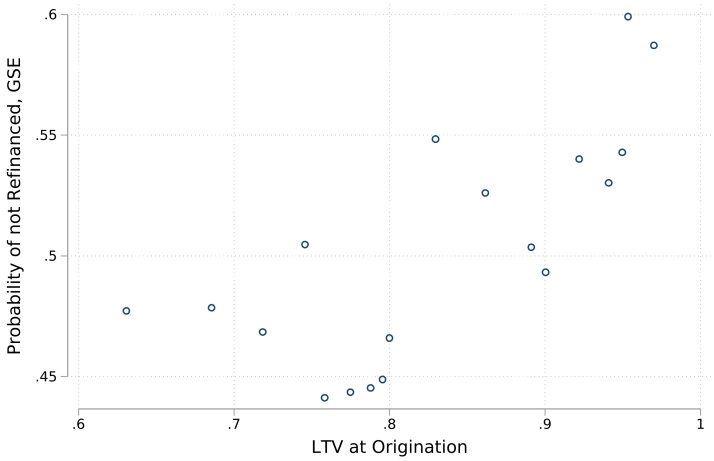
Panel C: Jumbo Loans



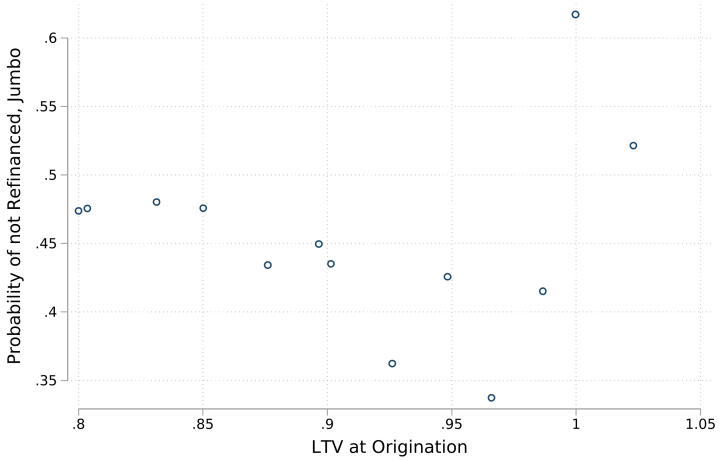
Note: These figures plot the bin scattered plot of the average probability of inaction in refinance for purchase loans originated after 2009. The y axis represents the average of a dummy variable equals 1 if the purchase loan have not refinanced until January 2022. The x axis represents Credit Score at application. Panel A plots for FHA loans and Panel B plots for GSE loans and Panel C plots for Jumbo Loans.

Figure B.2: Inaction in Refinance and LTV

Panel A: GSE

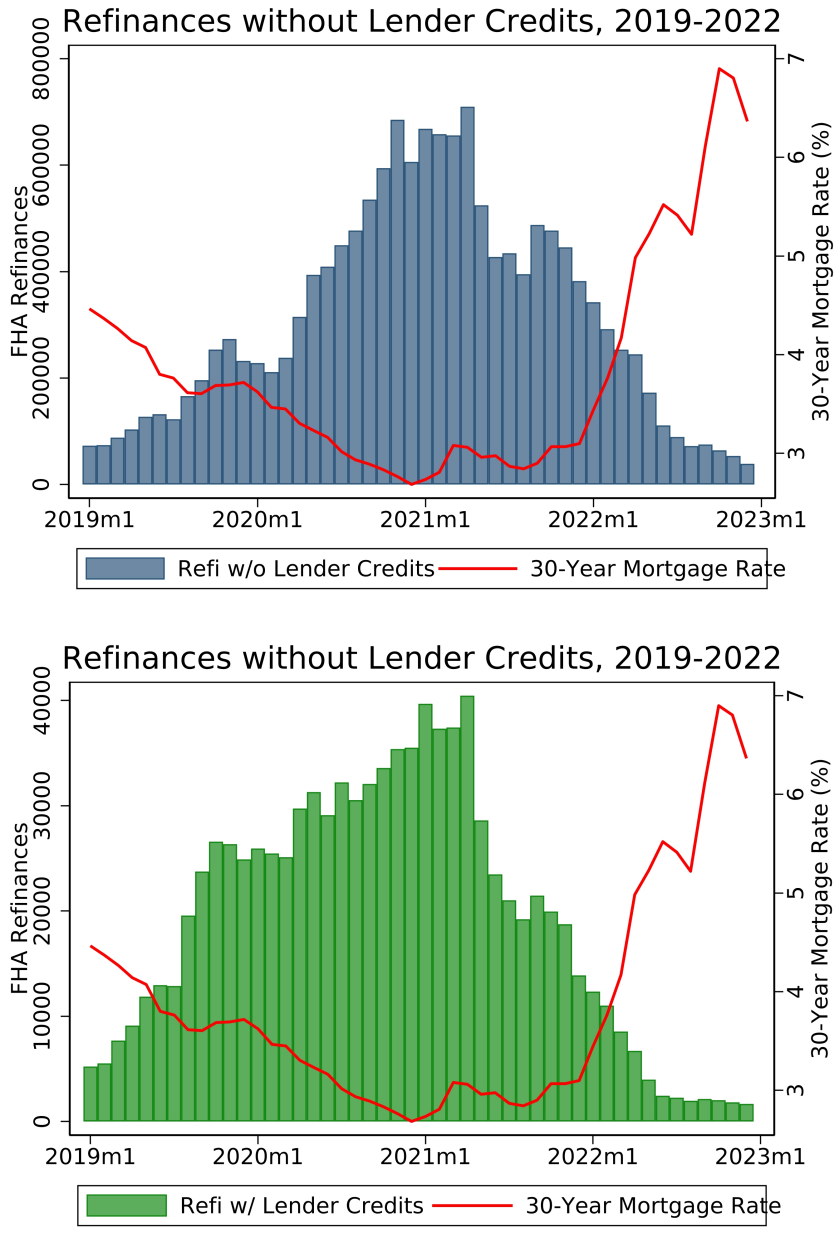


Panel B: Jumbo



Note: These figures plot the bin scattered plot of the average probability of inaction in refinance for purchase loans originated after 2009. The y axis represents the average of a dummy variable equals 1 if the purchase loan have not refinanced until January 2022. The x axis represents LTV at origination. Panel A plots for GSE loans and Panel B plots for Jumbo loans. Results for FHA loans are not reported because most of FHA loans have a LTV of 96.5% and there is little variation.

Figure B.3: Frequency of Refinances and Mortgage Rate, 2018-2022



Note: These figures plot the frequency of refinance and mortgage rate change, from 2019 to 2022. The x-axis is time (monthly). The y-axis on the left hand side is the frequency refinances. The y-axis on the right hand side is the 30 year mortgage rate reported in FRED. The top panel in dark blue bars represent the group who did not use lender credits; the bottom panel in green bars represent the group who used lender credits. Notice this graph is a different sample where we do not observe when the loan was originated, so the purchase loan can be originated anytime before 2018. The original purchase loan time and mortgage rate are not controlled for in these figures.

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