

Refinancing Inequality and Implications on Monetary Policy

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Abstract

I investigate the heterogeneous mortgage refinancing propensity across income groups and its effect on the refinancing channel of monetary policy. I document that low-income households refinance significantly less than high-income earners, a pattern referred to as “refinancing inequality.” This suggests that the refinancing channel does not effectively serve households that are most likely to be liquidity constrained. Despite its importance, this pattern and its effect on the policy channel have been understudied in the literature. I demonstrate refinancing inequality by expanding the time scope and incorporating control variables previously unconsidered in existing studies. On average, the bottom quintile households exhibit less than half the probability of refinancing compared to the top quintile. I also highlight refinancing inequality in terms of timing, revealing that lower-income households face greater delays. The estimated potential savings through refinancing are substantial, particularly for low-income households, amounting to more than 10% of their income. Furthermore, I show that as household income decreases, refinancing activity in response to monetary policy shocks significantly declines. These results suggest that the aggregate effect of expansionary policy could be larger if refinancing frictions were mitigated.

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1 Introduction

Mortgages play a key role in household finance due to their scale and prevalence. One of the most prominent features of the U.S. mortgage market is that it is dominated by long-term fixed-rate mortgages. As of February 2024, about 92% of all outstanding mortgages are fixed-rate. This market feature emphasizes the role of refinancing as a transmission channel of monetary policy. For example, when the Fed lower interest rates, mortgagors need to refinance their mortgages with lower rates, thereby accessing more liquidity to increase their consumption. At the same time, studies have identified significant friction in refinancing ([Keys et al. 2016](#); [Andersen et al. 2020](#); [Gerardi et al. 2023](#)) and it could significantly impair the effectiveness of monetary policy ([Beraja et al. 2019](#); [Defusco et al. 2019](#); [Defusco and Mondragon 2020](#)).

However, I document substantial refinancing heterogeneity across income groups *within* the average refinancing frictions. Low-income households engage significantly less in refinancing than high earners, a phenomenon referred to as “refinancing inequality.” This casts an important implication on monetary policy that the refinancing channel may not effectively serve households likely to be under liquidity constraints, described as “wealthy hand-to-mouth” by [Kaplan and Violante \(2014\)](#)¹. Despite this importance, refinancing inequality across income groups remains understudied in the literature. Furthermore, connecting the refinancing frictions to consumption response and quantifying their impact on monetary policy have not been explored in previous studies.

[Figure 1a](#) shows significantly varying refinancing activity by region in 2020, when there was a rapid fall in interest rates. [Figure 1b](#) provides a clearer picture, showing a positive correlation between regional average income and refinancing activity. In this study, we will utilize both characteristics observed in the plots. In the first part of the research, I will conduct

¹Specifically, the Heterogeneous Agent New Keynesian model (HANK) literature indicates that the lower the income relative to consumption (high average propensity to consume), the higher the marginal propensity to consume (MPC) (eg. [Auclert \(2019\)](#)). For more direct evidence, the 2022 American Community Survey (ACS) reports that over 98.9% of mortgagors with an annual income of \$2,000 or less are ‘cost-burdened,’ spending more than 30% of their income on housing costs. In contrast, 70.2% of households with an annual income between \$35,000 and \$50,000, 45.5% of households with an income between \$50,000 and \$75,000, and only 11.2% of households with an income above \$75,000 are cost-burdened. This clearly demonstrates that as absolute income increases, the proportion of income spent on housing decreases. Therefore, it can be reasonably inferred that lower-income households are likely to have less available liquidity.

a detailed analysis of the distinct correlation between income and refinancing as illustrated in panel (b). In the latter part of this study, I will exploit the regional heterogeneity in refinancing shown in panel (a) to identify the varying refinancing responses to monetary policy shocks by income.

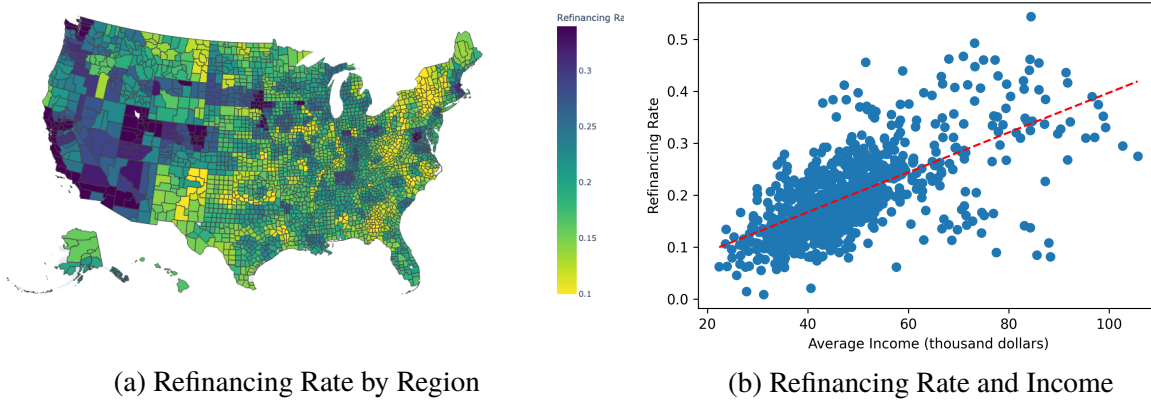


Figure 1: Refinancing Activity in 2020

My purpose in this article is to address the following questions: (1) How robust and generalizable is the pattern of refinancing inequality when controlling for other channels? (2) Can refinancing inequality serve as a significant friction in the transmission mechanism of monetary policy? To rigorously verify the preliminary evidence shown by the plot based on aggregate data, I adopted a micro-based analysis using loan-level panel data from 2000 to 2022. For each monthly observation of each loan, I estimated the interest rate obtainable upon refinancing and calculated the gap with the current rate to determine the financial profitability of refinancing (in-the-money). In addition, I matched refinanced (old) and refinancing (new) loans to overcome potential limitations of panel data. Using the national annual distribution of income at the time of origination, I divided each mortgage into quintiles and compared the refinancing probabilities. To study the effects of monetary policy shocks, I used a regional panel to analyze how these shocks affect refinancing responses across income quintiles.

I present three sets of main results. First, I document a substantial refinancing inequality across income groups. I start by examining the monthly refinancing probability based on the size of the interest rate incentive to refinance. Consistent with the existing literature,

substantial suboptimal refinancing was observed. However, when comparing the probability across income quintiles, I found a novel result: across all refinancing incentives, low-income households exhibited significantly lower refinancing probabilities compared to high-income households. Even after controlling for other channels that could induce refinancing frictions, the differences in refinancing probabilities across income quintiles remained significant. Next, I conducted a regression using a linear probability model. Similarly, despite including a series of control variables, the monthly refinancing probability for households in the lowest income quintile (2.2%) was less than half of that of households in the highest income quintile (4.9%) conditional on being in-the-money.

Second, I present that the potential savings from refinancing for low-income households are significant relative to their income. By matching refinanced (old) and refinancing (new) loans, I estimated the monthly payment reduction through refinancing. Households in the bottom and sub-bottom quintiles are estimated to be able to save about 11% to 12% of their monthly income through refinancing if they had done so. This is a substantial amount, not only due to its high proportion of their income but also because it represents a continuous increase in disposable income every month. Furthermore, if the income-induced refinancing frictions were reduced by half, it is estimated that an additional 8.1% of mortgagors in the bottom two income quintiles could have refinanced a year. Although this is a simple back-of-the-envelope estimate, it highlights the potentially significant effects of income-induced refinancing frictions on the monetary policy channel. Given that low-income households are more likely to have relatively low liquidity and a high marginal propensity to consume (MPC), we can anticipate that a reduction in refinancing inequality could significantly boost additional consumption.

Lastly, this study newly finds considerable heterogeneity in refinancing response to monetary policy changes. While identifying monetary policy shocks using high-frequency data, I present that the scale to which low-income households respond to interest rate shocks is significantly smaller than that of their high-income counterparts. To a one percent interest rate cut, the top quintile households refinance over 18% of total outstanding loans after seven quarters, whereas the bottom quintile refinances 9% of total loans. Furthermore, the size of the refinancing response consistently increased with higher income groups.

This paper contributes to two key areas of literature. The first explores refinancing frictions, where numerous studies since the financial crisis have shown that households often fail to refinance optimally ([Agarwal et al. 2015](#); [Keys et al. 2016](#); [Andersen et al. 2020](#); [Gerardi et al. 2023](#)). Common explanations for these sub-optimal decisions include closing costs, financial illiteracy, inattention, and racial discrimination. My analysis primarily uses the same data and methods as [Agarwal et al. \(2023b\)](#), who were the first to identify refinancing inequality and analyze income-level differences in refinancing. However, unlike their analysis, which focused solely on the COVID period, my analysis significantly expanded the time scope and included important control variables that were not considered, such as home equity and credit tightness. More importantly, I identified the pattern of refinancing inequality from new perspectives and obtained novel results. By analyzing refinancing patterns according to the size of the rate incentive, I demonstrated that inequality occurs across all incentive levels, thereby generalizing the findings. Additionally, I shed light on refinancing inequality from the angle of timing, showing that lower-income households experience more significant delays in refinancing.

The second strand of literature relates to the refinancing channel of monetary policy. A large body of research has highlighted that this channel significantly impacts the transmission of monetary policy ([Campbell and Cocco 2003](#); [Bhutta and Keys 2016](#); [Di Maggio et al. 2017](#); [Agarwal et al. 2018](#); [Chen et al. 2020](#); [Abel and Fuster 2021](#); [Agarwal et al. 2023a](#)). Furthermore, a number of previous studies have identified notable heterogeneity in this channel. The heterogeneity has been attributed to factors such as housing equity ([Beraja et al., 2019](#)), the path of past interest rates ([Berger et al. 2021](#); [Eichenbaum et al. 2022](#)), the type of mortgage contract ([Calza et al. 2013](#); [Di Maggio et al. 2017](#)), borrower's age ([Wong, 2019](#)), inaction ([Byrne et al., 2023](#)), and regulation changes ([Defusco et al. 2019](#); [Defusco and Mondragon 2020](#)). However, the role of income as a source of frictions in this channel remains underexplored. Motivated by this gap, this paper introduces a new policy implication: refinancing inequality could significantly undermine the effectiveness of the refinancing channel of monetary policy. By doing so, I was able to establish a direct link between refinancing inequality and monetary policy, illustrating dynamic heterogeneity in refinancing responses to interest rate shocks. To my knowledge, this is the first study to demonstrate the dynamic nature

of refinancing inequality in relation to monetary policy.

This paper briefly reviews the data and methodology in [section 2](#), then examines the average pattern of refinancing inequality over the entire period in [section 3](#) and provides a back-of-the-envelope analysis of potential savings that could have been gained by refinancing in [section 4](#). In [Section 5](#), the focus shifts to analyzing the refinancing dynamics in response to interest rate changes.

2 Institutional Background and Data

2.1 Effect of Income on Refinancing

The potential mechanisms by which income can influence refinancing can be outlined in three main ways. First, there is the friction caused by low liquidity and the presence of closing costs for low-income households. Closing costs typically include fees for the loan application, appraisal, title insurance, and other administrative services. It usually amounts to 2-5% of the loan balance, which can be a significant barrier to refinancing for households with low liquidity. If the borrower does not have immediate liquidity, it is usually possible to roll the closing costs into a new loan, though this presents a trade-off with the interest rate. The tradeoff entails deciding whether to pay higher upfront closing costs for a lower interest rate, reducing monthly payment over the loan term, or to opt for lower closing costs with a higher interest rate, resulting in higher monthly payments and total interest paid. [Appendix Figure A.2](#) shows an example of the trade-off between upfront cost and interest rate. In this example, it can be observed that for the same property and loan, both cash-out (equity extraction) and non-cash-out refinancing options are associated with a lower interest rate when higher upfront costs are incurred.

Secondly, there is the Payment to Income (PTI) ratio regulation. In the United States, the PTI level is applied as a soft borrowing constraint but is incorporated into the loan approval process by setting a standard. For example, the standard PTI level for a conventional loan is 36%, and a higher PTI level can only be approved if exceptional conditions such as a low LTV and a high credit score are met. As can be seen in actual data in [Table A.5](#), low-income households exhibit

higher PTI at loan origination compared to high-income households. Therefore, low-income households are more likely to hit the PTI limit than high-income households given the same distribution of idiosyncratic income shocks.

Lastly, there is the association with inattention. As shown by Andersen et al., inattention, which is a significant cause of observable suboptimal refinancing, is positively correlated with income. Consequently, through behavioral issues, different income groups may exhibit varying refinancing tendencies.

2.2 Data Overview

The primary dataset used in this study is the Freddie Mac loan-level panel data², which covers loans originating from 2000 to 2022. This dataset provides comprehensive information on both loan issuance and performance. The issuance data includes a rich set of loan and borrower characteristics at the time of origination. Key variables include the initial loan balance, loan term, interest rate, credit score, Loan-to-Value (LTV) ratio, Payment-to-Income (PTI) ratio, ZIP code, and estimated income. These variables allow for detailed analysis while controlling for factors influencing refinancing decisions, and I restricted sample to fixed-rate mortgages. In addition to issuance data, the performance data offers monthly observations of loans, which include the remaining balance, current interest rate, amortization, and prepayment status. This panel data enables the tracking of loan performance over time, facilitating a dynamic analysis of refinancing behavior.

The income for each loan can be back-calculated using Freddie Mac's issuance data, using the original interest rate, loan amount, maturity, and PTI information. Based on the distribution of this derived income of each origination year, the loans were then divided into quintiles.

To complement the Freddie Mac data, this study also utilizes data from the Home Mortgage Disclosure Act (HMDA)³ from 2000 to 2022. The HMDA data consists of detailed records on

²The Freddie Mac data set represents approximately 20%-30% of the total U.S. mortgage market, with the notable exclusion of "jumbo" loans, which are larger than the conforming loan limits set by the Federal Housing Finance Agency every year.

³The Home Mortgage Disclosure Act (HMDA) requires financial institutions to maintain and annually disclose data about home purchases, home purchase pre-approvals, home improvement, and refinance applications. The HMDA data captures the majority of mortgages in the U.S., accounting for about 92 percent of originations nationally in 2017,

individual mortgage applications and originations collected by financial institutions. The data include a wide array of information, such as the loan amount, type of loan, property location, borrower characteristics, and the outcome of the application. I matched Freddie Mac to HMDA using common variables to find corresponding loans, and used information from HMDA for analysis.

Detailed summary statistics of the final panel used in the analysis can be found in Appendix [subsection A.1](#).

2.3 Identifying Refinancing Loans

The main challenge when attempting to identify refinancing activity from the Freddie Mac loan panel is it only reports prepayment activity without a reason. As prepayment of mortgages could happen due to various other reasons than refinancing, such as moving or trading of houses, identifying refinancing is a key step for this analysis. I match a prepaid loan to a new loan also funded by Freddie Mac originated within a 45-day window of the closure of the prepaid loan⁴, following [Agarwal et al. \(2023b\)](#).

However, during the matching process, the restricted regional data of the publicly available Freddie Mac panel posed a significant challenge. The Freddie Mac data only provides three-digit ZIP codes for properties, which cover an excessively large area, leading to numerous duplicate matches and making unique matching infeasible. To address this issue, I matched the Freddie Mac data with HMDA data, utilizing the finer regional index at the census tract level provided by HMDA. Given the potential for bias in the matching processes, I performed a series of data validation checks, as displayed in the Appendix [subsection A.2](#), and found no significant errors in the matched sample compared to the population.

according to the Consumer Financial Protection Bureau.

⁴ The 45-day window is based on the institutional background of the rate lock period. A rate lock is an agreement between the borrower and the lender that guarantees a specified interest rate for a predetermined period while the mortgage application is being processed. The 45-day period is a common duration within this range. Thus, when a loan is prepaid for refinancing, a new loan is highly likely to be originated within this window.

2.4 Identifying In-the-money Loans

The decision for households to refinance is determined by the two types of incentives: first, the cash-out motive due to liquidity needs in response to idiosyncratic shocks, and second, the demand for reducing financing costs through lower mortgage rates. The first refinancing incentive is known to be insensitive to interest rates⁵, while the second incentive is directly affected by monetary policy. Since the focus of this study is to analyze the differences in the transmission of the benefits of accommodative monetary policy across income groups, the second incentive, the motive for interest rate reduction, should be emphasized. Therefore, distinguishing whether there is a financial benefit from lowering mortgage rates during refinancing is one of the key identifications. An in-the-money option refers to an option that provides a financial benefit when exercised. Therefore, a fixed-rate mortgage becomes an in-the-money loan when refinancing is financially advantageous.

$$\text{In-the-money if } \underbrace{(\text{Interest Rate}_i^{\text{old}} - \text{Potential Refi Rate}_{i,t}^{\text{new}}) - \text{Threshold}_{i,t}}_{\equiv \text{Rate Incentive}} > 0 \quad (1)$$

(i and t denote loan and time respectively)

The financial benefit of refinancing occurs when the gap between the contracted rate and the current market rate available through refinancing exceeds the threshold needed to cover refinancing costs, as shown in [Equation 1](#). The Potential Refi Rate varies by loan i and time t . While the contract rate remains fixed, the potential rate is crucial for identifying financial benefits. [Agarwal et al. \(2023b\)](#) assumed a uniform rate for all 30-year fixed-rate mortgages, but I refined this by estimating potential rates using observed refinances each quarter among borrowers with similar characteristics, following [Defusco and Mondragon \(2020\)](#). Specifically, refinances were categorized by credit score, LTV, state, origination quarter, and income quintile, resulting in 6,250 bins per quarter. The median interest rate in each bin was used as the potential refinance rate.

⁵ [Chen et al. \(2020\)](#) focused on the cash-out motive of refinancing and suggested that refinancing decisions of low-liquidity households are insensitive to interest rate changes.

The threshold refers to the minimum interest rate gap required for refinancing to be financially beneficial, taking into account both explicit and implicit costs associated with refinancing. It varies over time for each loan because the contracted interest rate and remaining balance vary by loan and time. I use the approximation suggested by [Agarwal et al. \(2013\)](#) to get the threshold.

$$Threshold_{i,t} = f(\rho, \lambda, \sigma, \kappa(M), M, \tau)$$

Here, ρ is the real discount rate, λ is the expected real rate of exogenous mortgage repayment due to factors such as relocation and death, σ is the standard deviation of the mortgage rate, $\kappa(M)$ is the tax-adjusted refinancing cost, M is the remaining real value of the mortgage, and τ is the marginal tax rate. This model assumes infinite mortgage maturity, an exogenous constant decline rate of the loan's real value, risk-neutral agents, and mortgage interest rates following a random walk⁶. The detailed formula is explained in [Appendix C](#).

It is worth noting that the threshold formula does not take into consideration heterogeneous interest rate expectations. For tractability, the real interest rate is assumed to follow a random walk. This assumption might be strong, as in the real world, refinancing decisions are heavily influenced by expectations of future interest rate paths. However, the pattern of refinancing inequality would still hold *conditional on* homogeneous expectation formation⁷. Furthermore, there is little evidence in the literature that expectations of interest rate paths vary by borrower's income.

⁶Regarding the random-walk mortgage rate, [Andersen et al. \(2020\)](#) noted that it closely approximates the behavior of standard long-term interest rate models. This is because Agarwal et al.'s (2013) model assumes no arbitrage opportunities, given that predictability in long-term interest rates would otherwise enable profits through mortgage transactions. This approach is widely accepted in the literature, with studies such as [Andersen et al. \(2020\)](#) and [Defusco and Mondragon \(2020\)](#) adopting this method.

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3 Evidence of Refinancing Inequality

3.1 Refinancing Probability by Rate Incentive

I begin the analysis by comparing differences in refinancing activity across income groups based on the size of the interest rate incentive. As discussed in the [subsection 2.4](#), the interest rate incentive captures the amount of profitability from refinancing, given the balance, current interest rate, and potential refi rate of each loan. It varies by loan and by month because the potential refi rate and threshold change over time within the same loan, as described in the [Equation 1](#).

Unconditional Refinancing Probability In the left panel of [Figure 2](#), the area to the right of zero in the x-axis indicates that the interest rate gap exceeds the in-the-money threshold, meaning the loan is in-the-money. Two prominent features can be observed. First, a significant degree of suboptimal refinancing is evident when the loan is out-of-money. This could be because refinancing includes cash-out (equity extraction), making it driven by household idiosyncratic shocks and less sensitive to interest rate changes ([Chen et al., 2020](#)). Second, as the incentive increases, a hump-shaped pattern emerges. There are two main reasons for this: firstly, active refinancers tend to refinance near the in-the-money threshold, leaving behind inactive borrowers over time. Secondly, it could be due to the likelihood of constrained mortgagors facing limitations such as LTV and PTI. Both the characteristics of the suboptimal refinancing and the hump shape of the plot are broadly consistent with the findings of [Andersen et al. \(2020\)](#) and [Defusco and Mondragon \(2020\)](#).

The right panel of [Figure 2](#) shows the refinancing probability divided by income quintile. Consistently across nearly all rate incentives, the lower income groups (bottom quintiles) exhibit significantly lower refinancing probabilities compared to the higher income groups (top quintiles). This difference is especially pronounced around the rate incentive 0.5 percentage points. This indicates that, despite refinancing being financially profitable, lower income groups are significantly less engaged in refinancing.

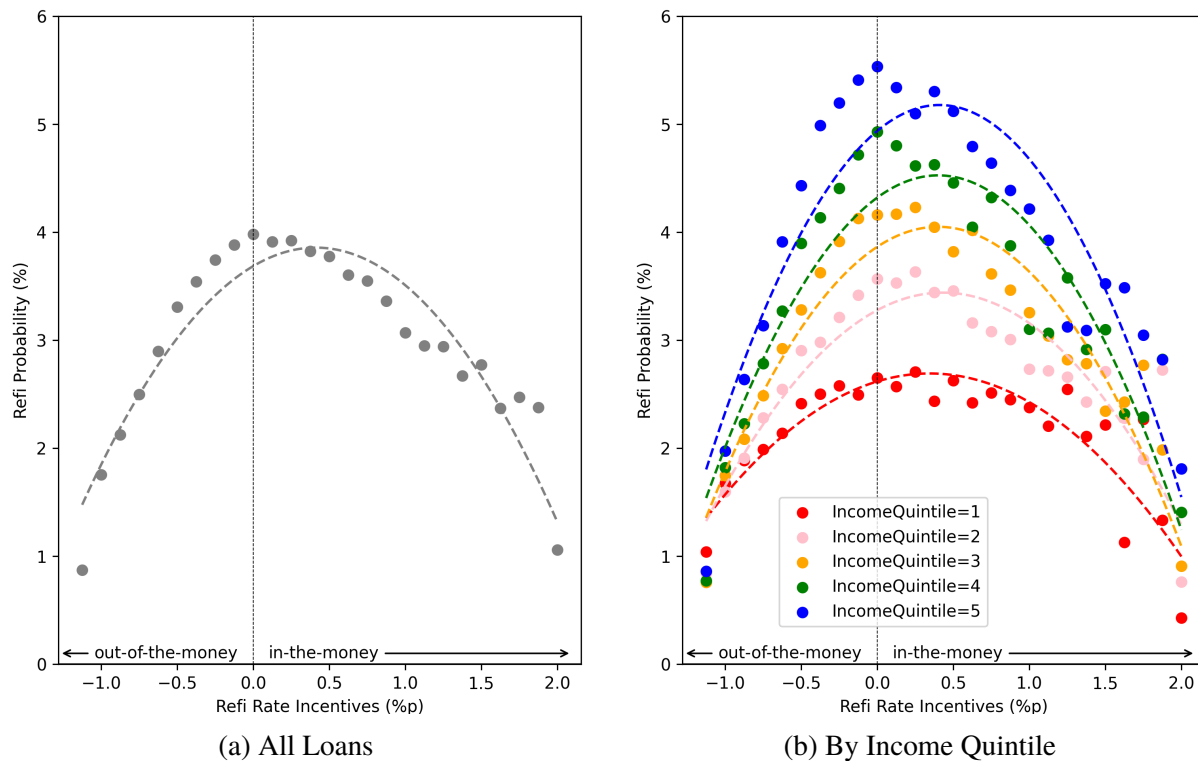


Figure 2: Refinancing Inequality by Rate Incentives

Notes: This plot shows the relationship between monthly refinancing probability and interest rate incentive. 'Refi Rate Incentive' is measured as the extent to which the gap between the current interest rate and the potential refi rate available through refinancing exceeds the financial profitability threshold for refinancing as suggested by [Agarwal et al. \(2013\)](#). On the x-axis, the right side of 0 indicates positive incentive (in-the-money), while the left side indicates negative incentive (out-of-the-money). Each dot represents the average refinancing probability within given 0.125-percentage point bins of the rate incentive. The panel (a) shows the average value for all income quintiles, while the panel (b) is calculated for each of the five income quintile groups of borrowers at the loan origination time.

Controlling for Other Variables One concern is that the difference in refinancing probabilities across quintiles could be driven by other factors. The control variables were included as categorical variables to allow for non-parametric regression⁸. To control for loan and borrower characteristics that are influential in refinancing, I used a rich set of control variables of credit score, loan age, loan balance to income ratio, and zip code, following [Agarwal et al. \(2023b\)](#).

However, existing research has not controlled for two other important variables that affect refinancing by income level. First, as highlighted in the literature by [Beraja et al. \(2019\)](#), the equity distribution channel could drive heterogeneous refinancing activities by income

⁸which variable?

group. For example, a low-income borrower would be more likely to purchase a home in a low-income area. If low-income areas are more susceptible to a decline in home prices during an economic downturn, the likelihood that the low-income borrower will become underwater increases, resulting in a lower ability to refinance. Such dynamic changes cannot be controlled by regional fixed effects. To address this, I controlled for the equity channel by estimating the loan-to-value (LTV) ratio for all loans on a monthly basis. Starting with the LTV and loan size at origination, I derived the collateral value and tracked home values monthly using the Zillow zipcode-level house price index. By combining the estimated home value with the observed remaining loan balance from the loan performance data, I was able to estimate the LTV for each loan each month. I controlled for the Home Affordable Refinance Program (HARP) in the same context. HARP was implemented from 2009 to 2018 to help borrowers with little or no equity in their homes refinance into more affordable mortgages. Because I matched the refinanced (old) and refinanced (new) loans, I was able to observe whether the new loan was refinanced through HARP, allowing me to control for the policy factor that affects the equity distribution channel.

Another potentially important factor that could lead to refinancing inequality is the differential impact of lender-side credit supply tightness across income groups. Just as credit supply expanded disproportionately for low-income households during periods of credit expansion (Mian and Sufi, 2009), tightening credit supply could differentially affect low-income borrowers. To address this issue, I include two control variables. First, quarterly changes in the credit tightness index from the Federal Reserve’s Senior Loan Officer Survey were used. Second, I controlled for loan application denial rates by income quintile derived from Home Mortgage Disclosure Act (HMDA) data. Using the same income quintile boundaries that were used in the main loan panel, HMDA applications were divided into five income groups, and I used annual changes in loan application denial rates of each income quintile.

$$RefiIndicator_{it} = \alpha + \sum_{Quintile \in J} \sum_{Bin \in K} \beta_j^k \cdot \mathbf{1}[RateIncentive_{it} \in k] + \Gamma' X_{it} + \epsilon_{it} \quad (2)$$

I controlled for all these variables using a non-parametric regression as specified in [Equation 2](#). $RefiIndicator_{it}$ is a indicator variable equal to 1 when the loan i is refinanced in month t . k denotes rate incentive bins and j is the five income quintile at the time of origination. $\mathbf{1}[RateIncentive_{it} \in k]$ is a dummy variable equal to 1 when the rate incentive falls in bin k , and X_{it} is a series of control variables.

The left panel of [Figure 3](#) shows the results of the unconditional probability regression without any controls. Compared to the right panel of [Figure 2](#), which displays the same unconditional probability, an additional observation is that the standard error bands widen significantly as the interest rate incentive exceeds 1.0. This suggests that most refinancing activity occurs in bins with rate incentives less than 1.0, and beyond that, the number of observations decreases.

The right panel of [Figure 3](#) displays the regression results including various control variables: LTV, credit score, loan age, zip code, credit tightness, HARP, loan balance to income ratio, and estimated LTV. Notably, even with the inclusion of extensive control variables, while the overall probability of refinancing decreases, income inequality remains substantial.

3.2 Regression Using a Linear Probability Model

To solidify the previous result, now I focus on the regression results of refinancing probability using the linear probability model (LPM)⁹. In this regression estimation, I analyzed only the loan observations that were in-the-money. The reason for this is that the focus of this study is on whether interest rate reductions lead to heterogeneous benefits across income groups, so refinancing unrelated to interest rate reductions is not of interest¹⁰. Specifically, I used the following specification:

⁹The LPM assumes a linear relationship between the dependent variable and the explanatory variables, but since I allowed for nonlinearity by using category variables for income quintiles, I found no significant differences compared to the logit results.

¹⁰For example, households who face idiosyncratic income shocks would refinance to extract equity regardless of interest rate, such as [Chen et al. \(2020\)](#) documented.

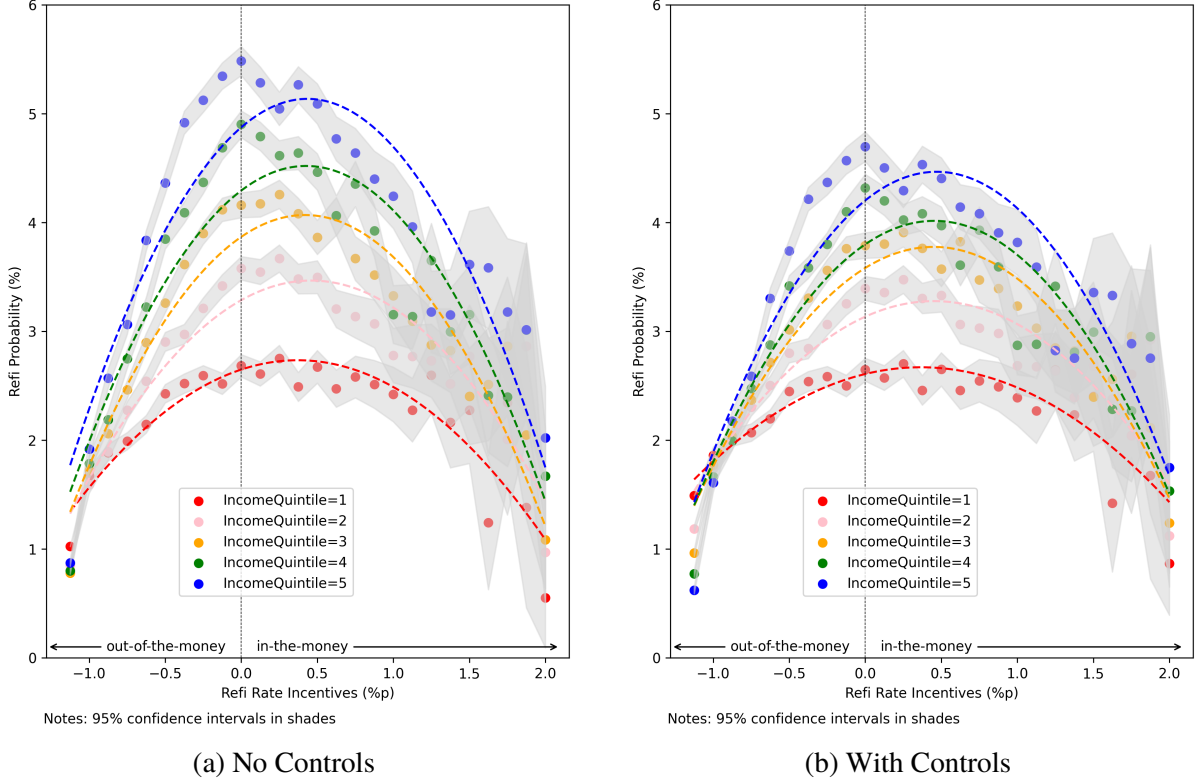


Figure 3: Refinancing Inequality by Rate Incentives with Controls

Notes: This plot shows the relationship between monthly refinancing probability and interest rate incentive using regression analysis with Equation 2. The panel (a) corresponds to the right panel of Figure 2 and illustrates the unconditional refinancing probability by income quintile. The panel (b) shows the refinancing probability by income quintile after controlling for the effects of control variables. Specifically, original LTV, loan age, ZIP code, credit supply tightness, HARP, and estimated LTV are controlled for. The shaded area represents the 95% confidence interval.

$$RefiIndicator_{it} = \alpha + \sum_{j=2}^5 \beta_j \cdot IncomeQuintile_i + \Gamma' X_{it} + \epsilon_{it} \quad (3)$$

Again, *RefiIndicator* is a indicator variable that has a value 1 if refinanced and 0 otherwise. j denotes the income quintile 2 to 5, and X_{it} is a series of control variables. In this regression estimation, I analyzed only the loan observations that were in-the-money. Therefore, the β_j means the refinancing propensity of income quintile j compared to the bottom quintile, conditional on being in-the-money.

The result of this regression is reported in Table 1. Column (a) shows the unconditional

Table 1: Heterogeneous Refinancing Propensity Across Income Groups

Dependent Equation	Refinancing Indicator $\times 100$				
	(1)	(2)	(3)	(4)	(5)
IncomeQuintile 2	0.716 ^a (0.0465)	0.604 ^a (0.0481)	0.629 ^a (0.0538)	0.784 ^a (0.0544)	0.790 ^a (0.0544)
IncomeQuintile 3	1.169 ^a (0.0475)	1.062 ^a (0.0502)	1.146 ^a (0.0568)	1.404 ^a (0.0585)	1.453 ^a (0.0585)
IncomeQuintile 4	1.586 ^a (0.0490)	1.486 ^a (0.0531)	1.601 ^a (0.0610)	1.953 ^a (0.0639)	2.048 ^a (0.0639)
IncomeQuintile 5	2.082 ^a (0.0516)	1.833 ^a (0.0569)	2.082 ^a (0.0670)	2.683 ^a (0.0743)	2.824 ^a (0.0744)
Constant	2.426 ^a (0.0325)	1.864 ^a (0.122)	2.085 ^a (0.124)	0.664 ^a (0.148)	0.537 ^a (0.148)
<i>Control variables</i>					
LTV, credit, loan age, rate inc., ZIP		x	x	x	x
Credit tightness, HARP			x	x	x
Loan balance to Income				x	x
Est. LTV					x
Observations	1,343,894	1,342,423	1,342,278	1,342,278	1,342,278
R-squared	0.002	0.010	0.011	0.011	0.012

Notes: Superscript a, b, c denote significance at 1%, 5%, 10% levels respectively. S.E. in parenthesis.

probability, indicating that the highest income quintile has a 2.3 percentage points higher monthly refinancing probability compared to the bottom quintile. The difference, excluding borrower/loan characteristics, slightly reduces to 1.9 percentage points, but as control variables are gradually added, the final base model in column (5) shows a 2.95 percentage points difference.

The predicted refinancing probability by income quintile, calculated using the same regression results, is shown in [Figure 4](#). The predicted probability illustrates the impact of differences in income quintiles on the final dependent variable when all control variables are at their mean values. Although there are some variations across quintiles with the addition of control variables, it is evident that the predicted probability increases clearly with income. Furthermore, the error bars, representing the 95% confidence intervals, confirm that the differences between quintiles are highly significant.

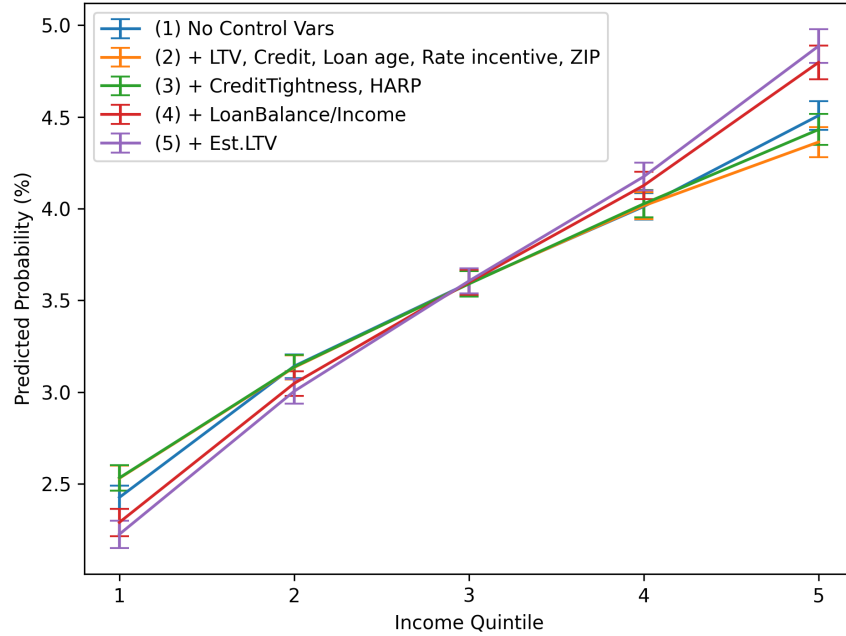


Figure 4: Predicted Refinancing Probability by Income Quintile

Notes: This plot shows the predicted monthly refinancing probability conditional on being in-the-money, using Equation 3. The 95% confidence intervals are represented by error bars and each line corresponds to the columns of the regression result in Table 1.

3.3 Robustness Checks

One of the major concerns is that since income quintiles are observed at the time of origination, changes in income quintiles at the time of refinancing might cause bias in regression results. Given that income quintile is a key variable, I performed four different robustness checks to validate the previous results.

First, I calculated the average loan age up to the refinancing point and used the Panel Study of Income Dynamics (PSID) data to track changes in mortgagors' income quintiles over the same period. In my sample, the average time to refinancing was 23 months. Therefore, I examined the changes in mortgagors' income quintiles over two years using the same yearly-changing income quintile thresholds. The probability of the lowest income quintile rising to the highest quintile after two years was 5.6%, while the probability of the highest quintile falling to the lowest quintile was 2.4%, both very low as suggested in Table B.8 ¹¹. Although the

¹¹Broadening the scope, the probability of the bottom two (1st and 2nd) income quintiles remaining in the same two quintiles after two years was 72.7%, whereas the probability of changing to the top two (4th and 5th) quintiles was

data's limitations prevent tracking income changes, these results suggest that my estimates are unlikely to be significantly distorted by frequent changes in income quintiles.

Second, my data panel matches old loans with new loans, allowing for the observation of income and other characteristics at the time of refinancing. Therefore, I was able to perform the same regression using [Equation 3](#) with income quintile and other control variables at the time of refinancing. The results confirmed that the pattern consistent with the benchmark regression was maintained. As shown in [Figure B.4a](#), even with an increase in control variables, the predicted refinancing probability for high-income households remained significantly higher than for lower income quintile groups¹².

Third, I conducted a regression analysis on only those loans where there was no change in income quintile between the new and old loans. The results still showed a clear refinancing inequality, as illustrated in [Figure B.4b](#). This indicates that the previous results hold even when excluding changes in income quintile.

Lastly, since the probability of changes in a borrower's income quintile is lower for loans with shorter ages, I conducted repeated regression analyses by varying the age of the sample loans. The results showed a clear refinancing inequality regardless of the loan age cut. [Figure B.5](#) illustrates the predicted probabilities from regression (5), which includes all control variables, analyzed by progressively widening the loan age range: less than one, two, three, five, and seven years. As the loan age sample increased from one year or less to two years or less, there was an overall increase in probability, causing a line shift. However, it was still evident that higher income was significantly associated with higher refinancing probabilities. The same pattern persisted when increasing the loan age limit further.

Other robustness checks using the Survey of Consumer Finance (SCF) can be found in the Appendix [subsection B.3](#).

12.6%. Conversely, the probability of the top two income quintiles remaining in the same quintiles was 81.6%, while the probability of falling to the bottom two quintiles was 8.2%, indicating a low likelihood.

¹²Note that this result is estimated based only on matched loans, excluding loans that were never refinanced. Therefore, the monthly refinancing probability is higher than in the benchmark regression. Also, the HARP variable, when based on new loans, showed that all loans were concentrated in quintiles 1 and 2. Controlling for this variable eliminated the differences between income quintiles. Therefore, it was not possible to control for the HARP variable.

3.4 Dynamics in Refinancing Decisions

The benchmark results analyzed heterogeneity in the average refinancing propensity across time. However, even if mortgages are in-the-money, there may be differences in the time it takes for each income quintile to refinance. For instance, borrowers in the low-income quintile might take several months longer to actually refinance after realizing their mortgages are in-the-money¹³, but ultimately, they might exhibit the same refinancing rate as high-income groups.

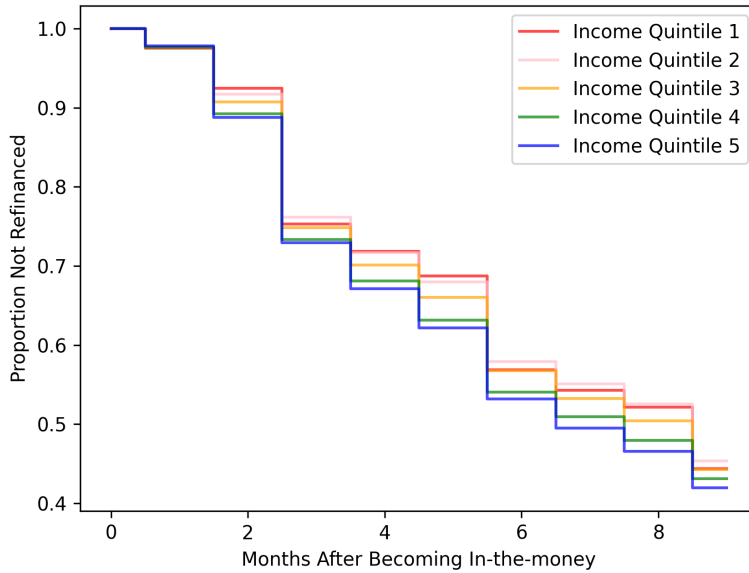


Figure 5: Proportion of Remaining Loans by Months After Becoming In-the-money

Notes: This plot shows the proportion of mortgages that remain not refinanced over time after becoming in-the-money. A loan can become out-of-money again within a few months after initially becoming in-the-money. In such cases, if the point at which the loan became in-the-money is within 12 months of the last in-the-money observation, it is considered part of the same sequence. If the out-of-money period exceeds 12 months, the in-the-money conversion point is reset.

To address this concern, first, I compared the cumulative refinancing over time after becoming in-the-money. The [Figure 4](#) aligns all loans at the point they become in-the-money and shows the proportion of mortgages remaining over time. At all times, the proportion of mortgages remaining for high-income groups is lower than that for low-income groups. For

¹³Low-income groups may take more time between loan application and origination due to lower access to financial institutions, weaker negotiating power, and the stringent scrutiny process by lenders.

instance, it took approximately 9 months for half of the bottom quintile's mortgages to be refinanced after becoming in-the-money, whereas it took only 7 months for the top quintile. This result tells us that the pattern of refinancing inequality persists regardless of the time taken.

Secondly, measuring the refinancing rate over a broader interval than monthly also showed consistent results. In particular, the refinancing rate was measured within three months after a loan became in-the-money and compared across groups, as shown in [Figure B.6](#). Even considering the potential differences in the time required for refinancing, it is confirmed that the low-income group exhibits a significantly lower refinancing rate compared to the high-income group.

In addition, expectations about the future path of interest rates can also be an important factor in determining the timing of refinancing. For example, during periods of declining interest rates, low-income groups may exhibit stronger diagnostic expectations compared to high-income groups, anticipating further rate drops and thus delaying refinancing. However, existing literature does not provide evidence of different patterns of diagnostic expectations across income groups. In this analysis, all income groups follow the identical expectation formation rule.

4 Potential Gains from Refinancing

Having identified significant refinancing inequality across income groups, I now investigate the extent to which this results in missed increases in disposable income. This study aims to examine how refinancing inequality ultimately impacts the monetary policy transmission channel, making the quantification of the saving amount crucial. I conducted the analysis on two main aspects: how much households' disposable income could have increased conditional on refinancing, and how many mortgages could have refinanced if income-induced friction were eased.

4.1 Potential Increase in Disposable Income Conditional on Refinancing

To start this analysis, I switched to a matched pair dataset of old and new loans. I analyzed how much each income group could reduce their interest rates through refinancing using a linear probability model. Using [Equation 3](#), I changed the dependent variable as the difference between the interest rate of the new loan and that of the old loan, leading to the specification of [Equation 4](#).

$$RateReduction_{it} = \alpha + \sum_{j=2}^5 \beta_j \cdot IncomeQuintile_i + \Gamma' X_{it} + \epsilon_{it} \quad (4)$$

The new interest rate after refinancing is generally lower than the existing one, negative beta values are expected. Since lower income quintiles typically have lower loan balances, a larger rate reduction is needed to offset the closing costs. Therefore, a larger absolute value of rate reduction is expected for lower income quintiles. As shown in [Figure A.1](#), the uncontrolled rate reductions of low quintile households are significantly larger than that of high-income groups, but the gap diminishes as more control variables are added.

Based on the estimated rate reductions, I performed a back-of-the-envelope calculation to estimate the potential savings. By subtracting the rate reduction attributed solely to income quintiles from the existing interest rates, I derived the new post-refinancing interest rates. Assuming all refinancings are done with a 30-year fixed-rate mortgage, I calculated the monthly payment reduction using these new estimated rates and examined this as a proportion of income.

The results showed that the bottom two income quintiles could save 11-12% of their monthly income through refinancing. This is a significant amount, as it represents additional disposable income occurring every month, not just a one-time saving.

4.2 Potential Extra Refinancing Activities

The next analysis examines how much refinancing itself could have increased if the frictions had been mitigated. [Table 3](#) shows the scenario where the gap between each income quintile and the

Table 2: Estimated Potential Gains from Refinancing

Income Quintile	Avg. Loan Balance at Refi (\$)	Est. Rate Reduction by Refi (%p)	New Interest Rate (%)	Mthly. Pymt. Reduction by Refi (\$)	Mthly. Pymt. Reduction to Income (%)
1	91,969.1	2.04	3.06	170.3	11.9
2	150,455.4	2.04	2.84	277.1	11.4
3	202,150.5	2.03	2.78	364.9	10.7
4	259,509.5	2.02	2.71	478.4	10.3
5	318,347.1	2.02	2.62	702.3	8.3

Notes: Assumed refinancing to 30-year FRM. Control variables are LTV, credit score, rate incentive, ZIP code, credit supply tightness, HARP, loan balance to income ratio, estimated LTV. The values are actual figures without inflation adjustment.

top quintile's probability halves, using [Figure 4](#)'s predicted monthly refinancing probability by income quintile. The assumption here is that the refinancing probability for the highest quintile is friction-free. This assumption, though somewhat strong, can be justified by considering that the gap of the estimated refinancing probabilities are primarily driven by income differentials, thereby controlling for the impact of income-induced friction faced by lower-income groups.

The next step was to estimate the number of in-the-money loans among the total outstanding loans. One important point to note is that the proportion of 'in the money' varies significantly with monetary policy. Therefore, to estimate under consistent monetary policy conditions, the sample was narrowed to after 2020.

Table 3: Estimated Extra Refinancing After 2020 with 50% Less Refi Friction

Quintile	Est. Refi Prob. Per Month		Share of In-the-money Loans (%)	Share of Extra Refi Loans Per Year (%)
	Current (%)	With 50% less friction (%)		
1	2.73	4.61	0.10	2.20
2	3.74	5.12	0.11	1.83
3	4.69	5.59	0.11	1.16
4	5.54	6.02	0.10	0.57
5	6.49	6.49	0.09	0.00

Notes: The estimated refinancing probability is based on [Equation 3](#) with observations after 2020. Control variables are LTV, credit score, rate incentive, ZIP code, credit supply tightness, HARP, loan balance to income ratio, estimated LTV.

I estimated the additional loans that could be refinanced assuming a 50% reduction in refinancing frictions. The results showed that around 1.8%-2.2% of mortgagors in the bottom two quintiles could additionally refinance per year. Therefore, if income-induced friction is

eased, a significant number of households could potentially benefit from further interest rate reductions. Moreover, considering the substantial potential increase in disposable income after refinancing, particularly significant among lower-income groups as shown in earlier analyses, it is anticipated that refinancing inequality will have a considerable impact on the transmission channel of monetary policy.

Based on the estimates, low-income households not only refinance significantly less despite the financial benefits, but also lose a substantial amount of additional disposable income as a result. Moreover, if the gap in refinancing inequality were to be reduced, a significant fraction of low-income households could potentially refinance.

5 Refinancing Response to Monetary Policy

The ultimate goal of this study is to examine whether the observed pattern of refinancing inequality impacts the monetary policy transmission mechanism. While the results so far have shown the *average* refinancing patterns across income groups over the period, it is necessary to assess the *dynamic* refinancing responses to changes in monetary policy to directly connect this pattern to monetary policy.

Figure 6 illustrates interest rates and mortgage prepayment activity over time. The 30-year fixed-rate mortgage interest rates closely follow the movements of the 30-year US Treasury rates, indicating a high pass-through of the Fed's monetary policy on mortgage rates. During periods of declining interest rates, significantly higher prepayment activity is observed. This suggests that prepayment activity is highly driven by refinancing to take advantage of lower borrowing costs. The most intriguing aspect is that the prepayment response varies substantially across income quintiles, especially during periods of declining rates. High-income households, based on origination income, exhibit significantly higher prepayment activity compared to low-income households. This suggests that the pass-through of mortgage rate cuts to household liquidity may differ significantly across income levels.

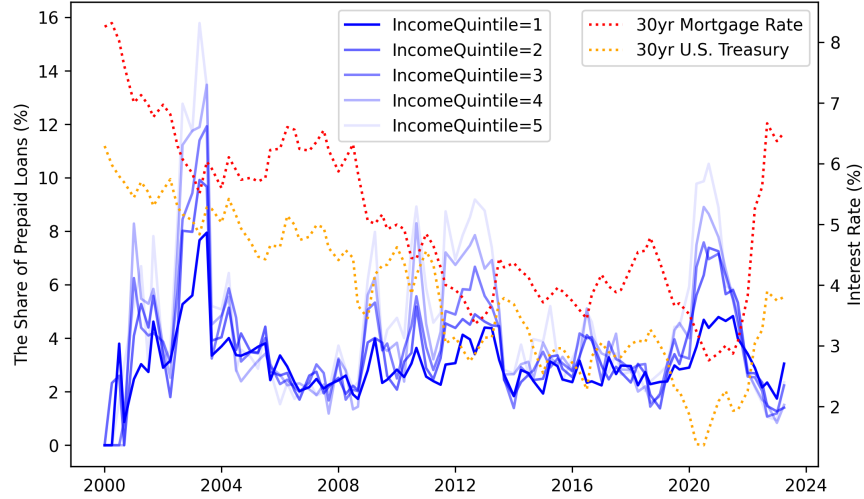


Figure 6: The Share of Refinanced Loans and Interest Rates

Notes: This plot shows the mortgage and US Treasury rates, as well as the share of prepaid mortgages from a 1% sample of Freddie Mac loans. Income quintiles are based on the national annual distribution of estimated incomes at the time of origination for Freddie Mac loans. To isolate policy effects, loans originated through HARP are excluded.

5.1 Data

To demonstrate refinancing inequality in a dynamic context, I examined the refinancing responses to exogenous monetary shocks across income quintiles. To do this, I followed the methodology of [Eichenbaum et al. \(2022\)](#) and used Freddie Mac panel data converted into regional data. The advantage of using regional aggregate data is twofold: first, it allows for the comparison and verification of results against established research; more importantly, it enables the use of the entire Freddie Mac population data rather than being limited to the old-new refinancing matched panel used in the previous analysis¹⁴. While the earlier panel used loan-level data to meticulously control for loan and borrower characteristics, this analysis focuses on refinancing responses in a macroeconomic context, making regional aggregate data appropriate. I constructed a regional panel using Freddie Mac data, consisting of quarterly numbers of outstanding and refinancing loans by income quintile for mortgages originated from

¹⁴Although refinancing information (reasons for prepayment) is not available at the loan level in the Freddie Mac data, which required me to match old and new loans to ensure that the loan was prepaid due to refinancing, it can be observed in the origination data. By aggregating the issuance data by region, I can use the entire dataset to derive the share of refinances relative to total outstanding loans.

2000 to 2019 across 908 three-digit ZIP code areas¹⁵.

For monetary policy shocks, I used the high-frequency shock data from [Swanson \(2021\)](#) to ensure exogeneity. Swanson recorded the changes in various asset prices within a 30-minute window around every FOMC meeting from 1991 to 2019. He then extracted the three largest principal components and demonstrated that these components correspond to changes in the federal funds rate, forward guidance, and large-scale asset purchases (LSAPs). A key advantage of this approach is that it addresses the limitations of high-frequency identification during the zero lower bound (ZLB) period. Since a significant portion of my data includes the ZLB period, Swanson’s shocks are particularly relevant.

I obtain aggregate time-series variables, including forecasts of unemployment, inflation, and GDP, from the Survey of Professional Forecasters (SPF). These variables were used to control for the information channel suggested by [Nakamura and Steinsson \(2018\)](#). Also, to control for house prices, I used the Zillow zipcode-level house price index.

In this analysis, the key variable is the refinancing propensity. I compute this by measuring the cumulative proportion of refinanced loans from outstanding loans at the regional level as below:

$$\rho_{t+h}^{r,j} = \frac{x_t^{r,j} + \dots + x_{t+h}^{r,j}}{(y_t^{r,j} + \dots + y_{t+h}^{r,j})/h} \quad (5)$$

Here, $x_t^{r,j}$ is the number of refinancing loans by income quintile j in region r in quarter t , $y_t^{r,j}$ is the number of all outstanding loans, and h is the analysis time horizon.

5.2 Regression Results

Average Refinancing Response to Monetary Policy Shocks I begin by examining the average refinancing response for all income groups, in comparison with existing research. I start by considering the local projection analysis suggested by [Jordà \(2005\)](#).

¹⁵However, the actual analysis used data from 2004 onwards. This is because Freddie Mac data provides information only on loans originated from 2000 onwards, leading to insufficient cumulative loan data by income quintile up to 2003. Therefore, to prevent outlier values in income quintile refinancing rates, a sort of burn-in period was necessary.

$$\rho_{t+h}^r = \beta_0^h X^r + \beta_1^h \Delta R_t^{IV} + \beta_2^h Z_t^r + \beta_3^h Z_t + \text{Lags}_t^r + \epsilon_t^z \quad (6)$$

Here, X^r represents a vector of region fixed effects, and ΔR_t^{IV} denotes an instrument variable for interest rate *falls* using high-frequency shocks. The interest rate is transformed to a positive sign indicating a decrease in interest rates. Therefore, we expect a positive response of refinancing. Z_t^r includes regional control variables such as changes in unemployment rates and house prices. The vector Z_t denotes a set of time-varying controls, specifically including a two-year ahead horizon, the civilian unemployment rate (also two years ahead), and the CPI inflation rate (forecasted for both one and two years ahead). I used three lags terms for all variables.

First, I begin the analysis by demonstrating the strong impact of monetary policy on mortgage interest rates. [Table 4](#) presents the first-stage estimates. All three high-frequency factors exhibit a significant positive correlation with the 30-year fixed mortgage interest rate. In particular, the effect of LSAP, which involves the purchase of long-term bonds, has the largest impact on the 30-year fixed mortgage rate, aligning with expectations. The negative relationship between rising expectations for GDP and CPI and the actual mortgage rate reduction effect is consistent with economic interpretation, as higher expectations for GDP and CPI reduce the real impact of mortgage rate cuts. The F test for the joint significance of the regression coefficients is greater than ten.

[Figure 7](#) shows the average refinancing response to a 1% interest rate falls. It indicates that cumulatively 20% of all mortgages are refinanced 7 quarters after the shock. After the seventh quarter, the cumulative ratio decreases because new mortgages increase the total number of outstanding loans while the number of refinancing decreases, gradually lowering the ratio below the unconditional ratio. Although the types of mortgages covered by the data and the sample periods differ from [Eichenbaum et al. \(2022\)](#)'s results, which show about 15-25%¹⁶ refinancing by the fifth quarter following an interest rate shock, my result is largely consistent with their

¹⁶They estimated the refinancing rate depending on the interest rate gaps between existing loans and the market rate, which makes the estimated range larger.

Table 4: First-stage Estimates

Dependent		Δ Real Mortgage Rates of 30-year FRM	
High-frequency Factors		Survey of Professional Forecasters	
- FFR	0.0165 ^a (0.00)	- Δ GDP (2 yrs)	-0.0341 ^a (0.00)
- Forward Guidance	0.0290 ^a (0.00)	- Unemp. (2 yrs)	0.0273 ^a (0.00)
- LSAP	0.0344 ^a (0.00)	- CPI (1 yrs)	-0.0347 ^a (0.00)
Δ House Price	0.0005 ^a (0.00)	- CPI (2 yrs)	-0.0832 ^a (0.01)
Constant	0.0427 ^a (0.02)	Unemp.	0.00641 ^a (0.00)
Observations	46,351	F-statistic	2,803.820
R-squared	0.358	Prob. > F	0.000

Notes: Superscript a, b, c denote significance at 1%, 5%, 10% levels respectively. S.E. in parenthesis.

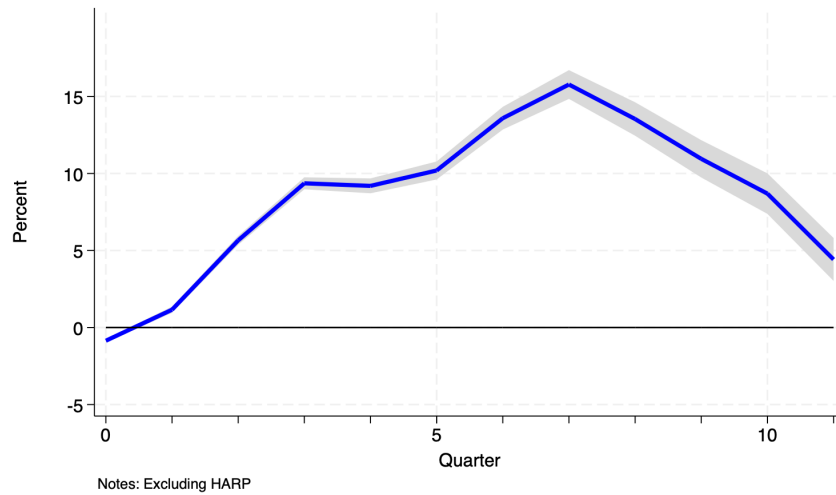


Figure 7: Cumulative Average Refinancing Response to a 1% Interest Rate Cut

Notes: This plot shows the cumulative refinancing response of all income groups to 1% interest rate falls using Equation 6. The dependent variable is the cumulative proportion of loans refinanced in each region as described in Equation 5. Regions are 908 three-digit ZIP code, and quarterly data from 2004 to 2022 was used. The shading represents the 95% confidence interval.

findings.

Heterogeneous Refinancing Response Across Income Groups Now, I will examine the heterogeneous refinancing responses across different income levels, which is the primary

focus of this chapter. By modifying the Equation 6 I consider following specification:

$$\rho_{t+h}^{r,j} = \beta_0^h X^r + \beta_1^h \Delta R_t^{IV} + \beta_2^h Z_t^r + \beta_3^h Z_t + Lag s_t^{r,j} + \epsilon_t^z \quad (7)$$

While the meaning of each variable remains the same as in Equation 6, the dependent variable, which is the proportion of refinanced loans, was analyzed separately for each income level. Figure 8 illustrates the refinancing response by income quintiles to a 1% interest rate reduction. Seven quarters after the interest rate reduction, households in the highest income quintile show a cumulative refinancing rate of approximately 25%, surpassing the average refinancing rate of 20% observed earlier. In contrast, households in the bottom two income quintiles have peak cumulative refinancing rates of about 15% and 8%, respectively, significantly lower than their wealthier counterparts.

There are other specifications to measure the dependent variable of the refinancing proportion. As explained in the Appendix subsection B.4, I conducted robustness checks using different specifications and the pattern of refinancing inequality was robust across all specifications.

6 Conclusion

This paper presents evidence that heterogeneous refinancing propensities across income groups can significantly impact the transmission effects of monetary policy. Using a broader time series and more robust measures than previous studies, this research shows the low-income households significantly less engage in refinancing inequality than high-income households. Additionally, it demonstrates that the potential increase in disposable income through refinancing is particularly substantial for low-income groups. By analyzing the refinancing response to monetary policy shocks across income quintiles, the study shows that refinancing inequality persists in a dynamic context. These findings suggest that if the friction of refinancing inequality is mitigated, the real effects of expansionary monetary policy could be amplified.

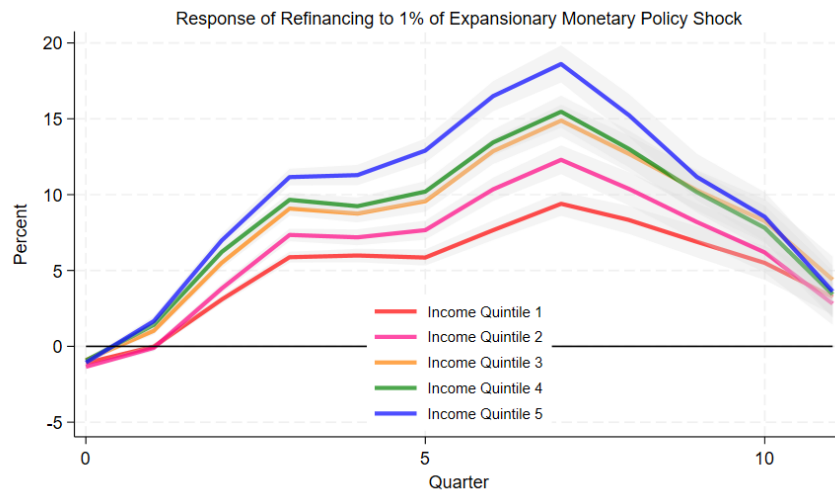


Figure 8: Cumulative Refinancing Response to a 1% Interest Rate Cut by Income Quintile

Notes: This plot shows the cumulative refinancing response by income quintile to 1% interest rate falls using Equation 7. The dependent variable is the cumulative proportion of loans refinanced in each region and income group as described in Equation 5. Regions are 908 three-digit ZIP code, and quarterly data from 2004 to 2022 was used. The shading represents the 95% confidence interval.

A Appendix: Tables and Figures

A.1 Figures and Tables

Table A.5: Mean Values by Income Quintile

Income Quintile	Loan ID (count)	Credit Score	LTV (%)	PTI (%)	Initial Loan Balance (\$)
1	90,331 <24.1>	744.3 (246.7)	69.1 (20.4)	39.5 (8.7)	113,079.9 (48,140.0)
2	78,577 <21.0>	746.9 (201.9)	72.8 (17.5)	36.9 (9.2)	180,094.7 (65,313.4)
3	73,251 <19.5>	750.1 (181.9)	73.4 (16.6)	35.1 (9.6)	236,640.2 (88,343.2)
4	68,386 <18.2>	756.5 (220.8)	73.1 (16.1)	32.7 (9.7)	299,712.5 (113,507.7)
5	64,332 <17.2>	765.6 (235.0)	69.9 (16.4)	25.5 (9.5)	368,110.3 (144,937.8)
Total	374,877 <100.0>	751.8 (219.6)	71.5 (17.8)	34.5 (10.4)	228,178.7 (130,095.4)
Income Quintile	Maturity (Month)	Income (\$)	Monthly Payment (\$)	House Value (\$)	
1	328.8 (66.1)	18,251.7 (5,230.7)	595.0 (205.7)	180,890.9 (106,661.4)	
2	325.2 (68.7)	30,718.6 (4,457.3)	943.4 (263.5)	264,049.8 (132,821.6)	
3	323.6 (70.0)	42,484.3 (5,611.8)	1,239.8 (366.4)	341,449.0 (172,616.7)	
4	319.7 (72.8)	58,208.9 (8,015.1)	1,578.9 (488.9)	431,965.9 (214,241.4)	
5	301.9 (82.9)	103,865.1 (58,277.9)	2,026.4 (715.0)	562,296.5 (305,448.9)	
Total	320.8 (72.3)	47,369.5 (38,036.0)	1,214.4 (654.4)	339,725.3 (232,158.2)	

Notes: The table reports means and standard deviations (in parentheses) by income quintile. The Loan ID column represents the unique number of loans, and the values within the angle brackets indicate the proportion of loans within that quintile relative to the total number of loans. Unconditional income quintiles are divided into 20% segments each, but the matched panel is based on matched refinanced loans. Therefore, the proportion of the matched panel can vary according to the number of refinanced loans in each income quintile.

Table A.6: Interest Rate Reductions by Refinancing

Dependent Equation	Interest Rate Reduction by Refi (%p)				
	(1)	(2)	(3)	(4)	(5)
IncomeQuintile 2	-0.186 ^a (0.00317)	0.0108 ^a (0.00273)	0.0166 ^a (0.00293)	0.000147 (0.00298)	0.000926 (0.00296)
IncomeQuintile 3	-0.294 ^a (0.00320)	0.0134 ^a (0.00283)	0.0216 ^a (0.00307)	-0.00529 ^c (0.00319)	-0.00741 ^b (0.00317)
IncomeQuintile 4	-0.370 ^a (0.00328)	0.0141 ^a (0.00297)	0.0249 ^a (0.00324)	-0.0112 ^a (0.00345)	-0.0176 ^a (0.00343)
IncomeQuintile 5	-0.446 ^a (0.00342)	0.0296 ^a (0.00319)	0.0440 ^a (0.00350)	-0.0133 ^a (0.00402)	-0.0198 ^a (0.00400)
Constant	2.283 ^a (0.00229)	0.963 ^a (0.00701)	0.949 ^a (0.00709)	1.059 ^a (0.00846)	1.045 ^a (0.00843)
<i>Control variables</i>					
LTV, credit score, loan age, ZIP code		x	x	x	x
Credit tightness, HARP			x	x	x
Loan balance to Income				x	x
Est. equity					x
Observations	482,078	481,683	481,683	481,683	481,683
R-squared	0.043	0.351	0.352	0.354	0.361
Equation	Predicted Interest Rate Reduction by Refi (%p)				
	(1)	(2)	(3)	(4)	(5)
IncomeQuintile 1	2.2828 (0.0023)	2.0202 (0.0021)	2.0147 (0.0021)	2.0405 (0.0022)	2.0434 (0.0022)
IncomeQuintile 2	2.0965 (0.0022)	2.0310 (0.0019)	2.0319 (0.0019)	2.0415 (0.0019)	2.0444 (0.0019)
IncomeQuintile 3	1.9888 (0.0022)	2.0337 (0.0019)	2.0353 (0.0019)	2.0345 (0.0019)	2.0349 (0.0019)
IncomeQuintile 4	1.9128 (0.0024)	2.0344 (0.0020)	2.0370 (0.0020)	2.0268 (0.0020)	2.0234 (0.0020)
IncomeQuintile 5	1.8372 (0.0025)	2.0498 (0.0022)	2.0524 (0.0022)	2.0204 (0.0025)	2.0163 (0.0025)

Notes: This table presents estimated interest rate savings through refinancing using Equation 4. The upper section of the table displays the regression results, while the lower section shows predicted values of the dependent variable based on the regression results. Superscripts a, b, c denote significance at 1%, 5%, 10% levels respectively. S.E. in parenthesis.

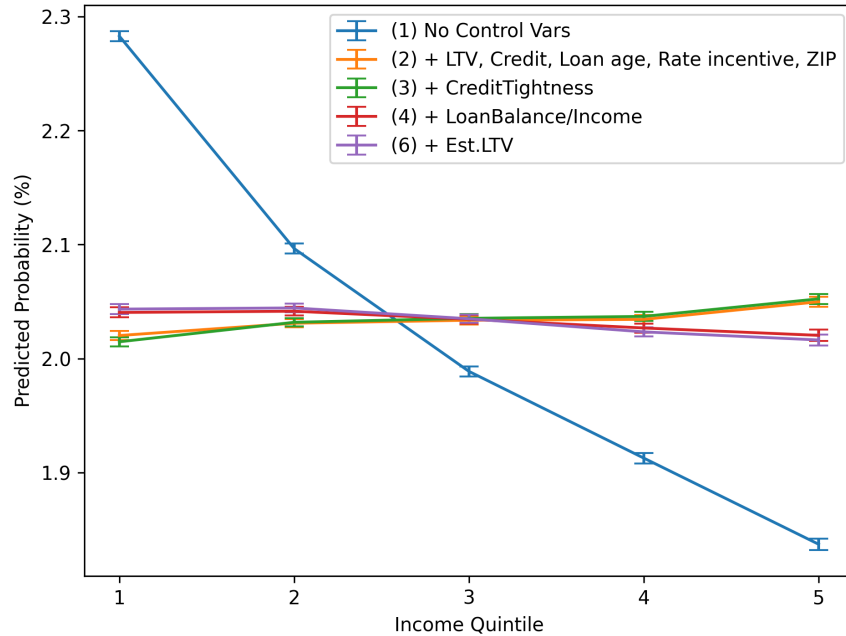


Figure A.1: Predicted Interest Rate Reduction from Refinancing

Notes: This plot shows the interest rate reductions due to refinancing across income quintiles, as estimated by Equation 5. The 95% confidence intervals are represented by error bars and each line corresponds to the columns of the regression result in Table A.6.

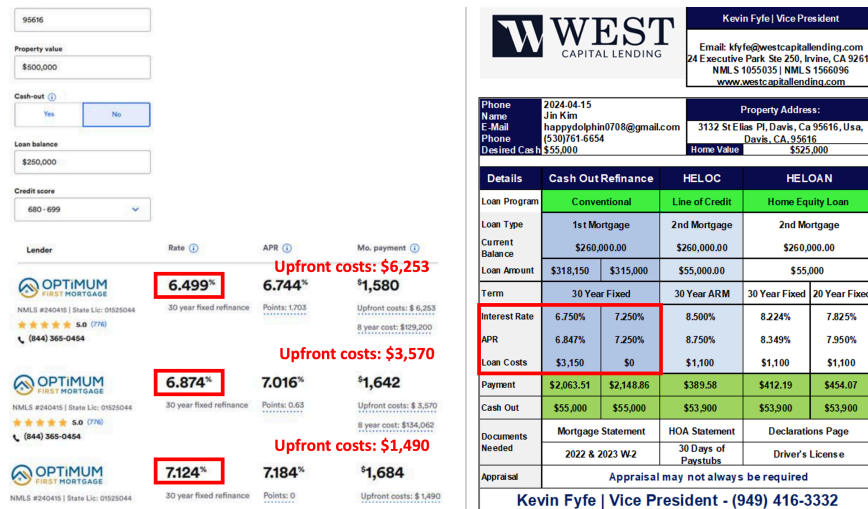


Figure A.2: Predicted Interest Rate Reduction from Refinancing

Notes: This figure shows the offers received from mortgage brokers in a hypothetical scenario for refinancing a home in Davis, California, as of May 2024. The left figure assumes pure rate refinancing (non-cash out), while the right figure assumes a cash-out scenario. Both figures illustrate the tradeoff between upfront costs and interest rates.

A.2 Data Validity Checks

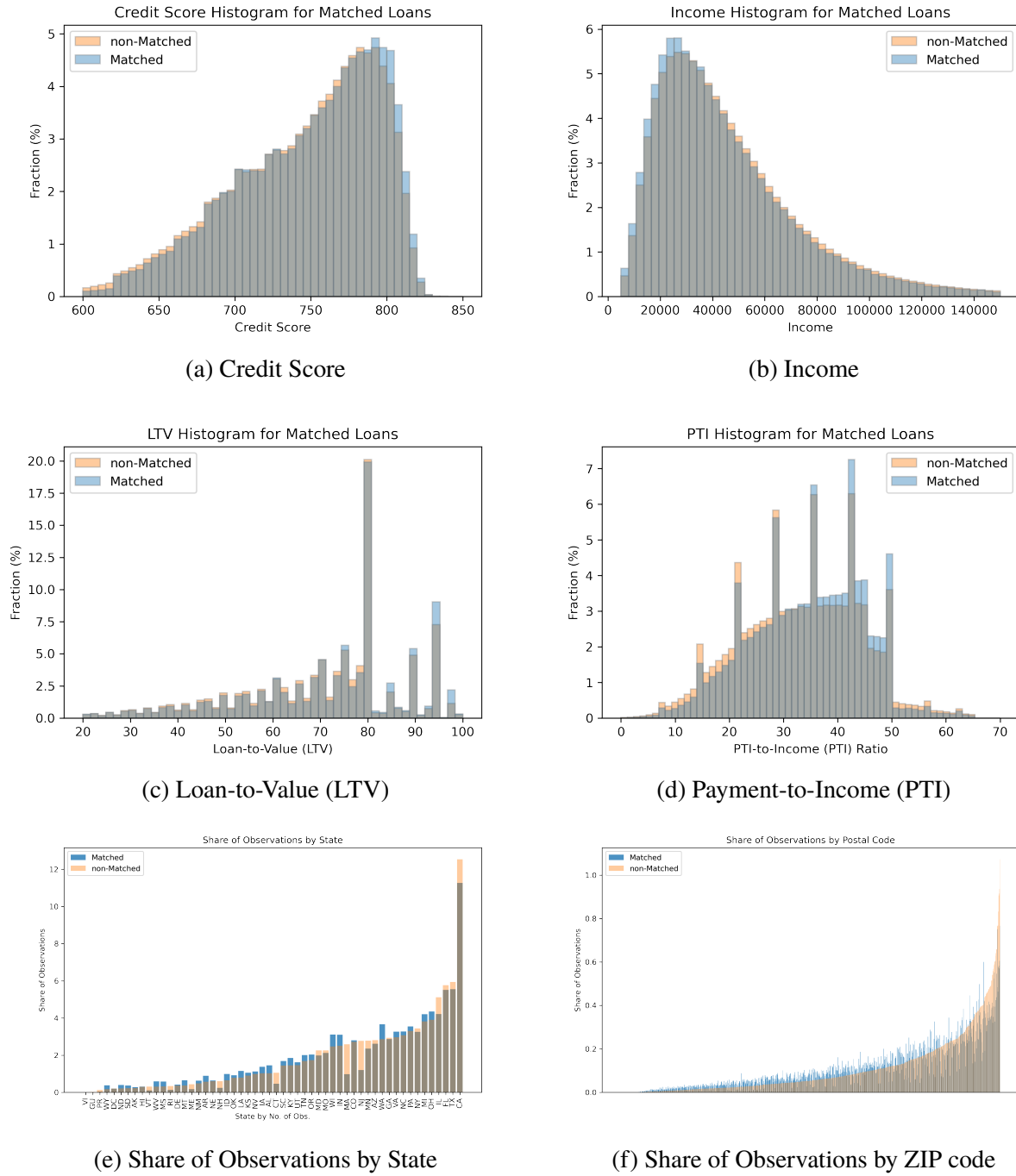


Figure A.3: Matched and Non-Matched Data Comparison by Distribution of Key Variables

Table A.7: Data Validity Checks on the Matched Panel

	Loan ID (count)	Credit Score	Loan Balance	Loan Term	Income	LTV	PTI
Matched Panel (mean)	374,877	751.8	228,179	320.8	47,369	71.5	34.5
All (mean)	41,150,001	758.4	213,022	309.4	49,514	70.1	33.3
Difference	<i>0.9% of total</i>	-0.9%	7.1%	3.7%	-4.3%	2.0%	3.5%
Matched Panel (median)	374,877	757.0	202,000	360.0	38,829	76.0	35.0
All (median)	41,150,001	754.0	184,000	360.0	40,474	75.0	34.0
Difference	<i>0.9% of total</i>	0.4%	9.8%	0.0%	-4.1%	0.0%	2.9%

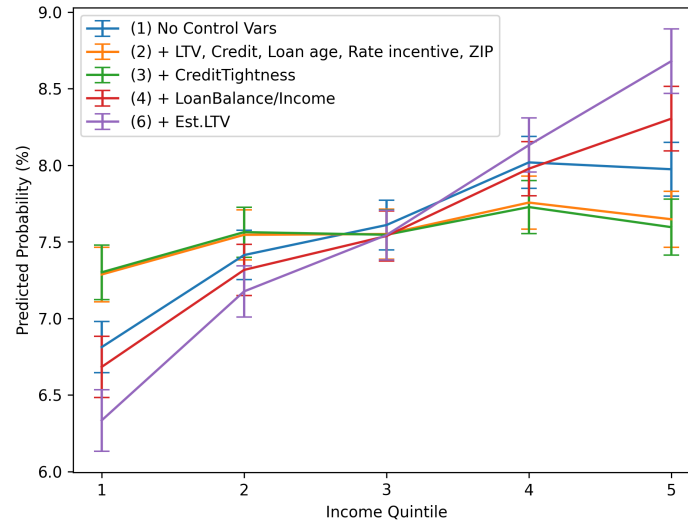
B Appendix: Robustness Checks

B.1 Changes in Income Quintile

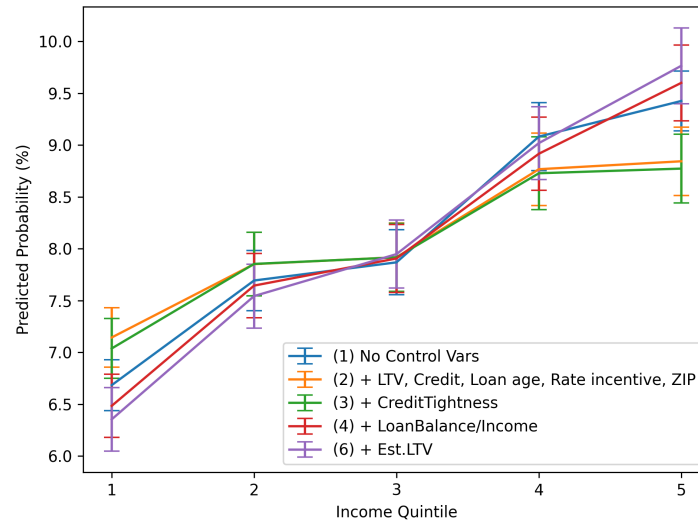
Table B.8: Income Quintile Transition Matrix

Data	Income Quintile	To 1	To 2	To 3	To 4	To 5	Total (%)
PSID ¹	From 1	68.9	14.8	6.8	4.0	5.6	100.0
	2	26.2	35.7	22.6	9.6	6.0	100.0
	3	12.6	17.8	33.2	24.9	11.5	100.0
	4	4.7	7.6	17.2	38.6	31.9	100.0
	5	2.4	1.6	3.2	10.0	82.7	100.0
Loan Panel ²	From 1	43.6	24.6	15.0	10.0	6.8	100.0
	2	20.9	30.4	22.7	15.4	10.7	100.0
	3	9.3	22.4	28.9	23.1	16.3	100.0
	4	4.9	11.4	22.8	33.4	27.5	100.0
	5	2.9	6.1	13.0	25.6	52.4	100.0

Notes: 1) Panel Study of Income Dynamics. Changes of mortgagor's income over two years, 2005-2021 data, 2) Changes from origination to refinancing.



(a) Predicted Refinancing Probability Using New Loan's Information



(b) Predicted Refinancing Probability for Loans Without Income Quintile Changes

Figure B.4: Refinancing Propensity by Income Quintile and Leverage Ratio

Notes: Panel (a) shows the predicted monthly refinancing probability conditional on being in-the-money, using new loan information at the time of refinancing. Panel (b) shows the same probability using samples restricted to loan pairs where the income quintile did not change from origination to refinancing. These regressions are based on Equation 3. Additionally, they are based on matched loans, excluding those that were never refinanced, which leads to a higher monthly refinancing probability than the benchmark regression. The 95% confidence intervals are represented by error bars.

Table B.9: Regression by Loan Age Restrictions

Dependent Loan Age ≤	Refinancing Indicator x 100			
	1 yr	2 yrs	3 yrs	5 yrs
IncomeQuintile 2	0.561 ^a (0.245)	1.220 ^a (0.146)	1.229 ^a (0.0951)	0.962 ^a (0.0732)
IncomeQuintile 3	1.235 ^a (0.250)	1.963 ^a (0.153)	2.041 ^a (0.102)	1.741 ^a (0.0783)
IncomeQuintile 4	2.192 ^a (0.259)	2.875 ^a (0.161)	2.752 ^a (0.111)	2.403 ^a (0.0854)
IncomeQuintile 5	2.912 ^a (0.292)	3.642 ^a (0.180)	3.654 ^a (0.127)	3.283 ^a (0.0981)
Constant	0.276 (0.589)	-0.373 (0.354)	-0.244 (0.263)	-0.0230 (0.200)
Observations	97,515	374,996	670,264	945,099
R-squared	0.022	0.015	0.014	0.012

Notes: a, b, c denote significance at 1%, 5%, 10% levels respectively. S.E. in parenthesis. The results base on the benchmark regression (5); control variables are LTV, credit score, rate incentive, credit tightness, HARP, loan balance to income, estimated LTV.

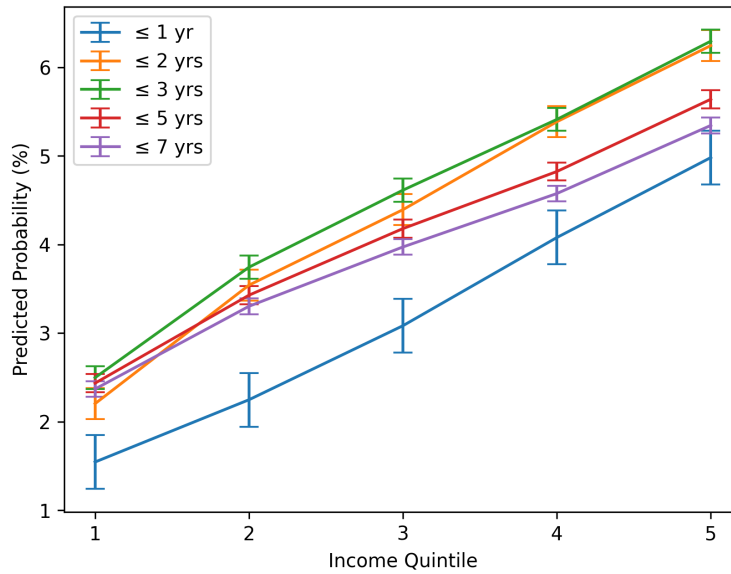


Figure B.5: Predicted Refinancing Probability by Loan Age

Notes: This plot shows the predicted monthly refinancing probability by loan age, using Equation 3. The results are based on the benchmark regression (5); control variables are LTV, credit score, rate incentive, credit tightness, HARP, loan balance to income, and estimated LTV. The 95% confidence intervals are represented by error bars.

B.2 Dynamics in Refinancing Decisions

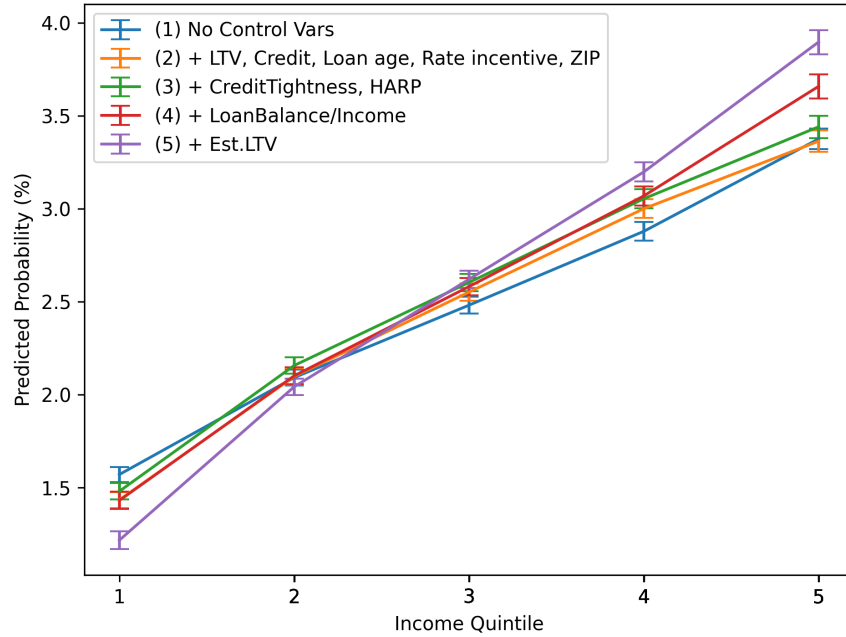


Figure B.6: Predicted Refinancing Probability with a Three-month In-the-money Window

Notes: This plot shows the predicted monthly refinancing probability by income quintile, using [Equation 3](#). Unlike the benchmark regression, here we estimate the probabilities, assuming that once in-the-money, it remains in-the-money for the next three months. In other words, this result is calculated by extending the refinancing window from one month to three months, considering that it may take longer for lower-income households to actually refinance after recognizing that they are in-the-money, compared to higher-income households.

B.3 Survey of Consumer Finances (SCF)

Finally, I utilized the Survey of Consumer Finances (SCF) to examine whether the pattern of refinancing inequality could be observed. While the SCF does not provide panel data and is conducted as a triennial survey, it allows us to observe the year of the most recent refinancing for currently held mortgages. This enables us to derive annual refinancing rates.

[Figure B.7](#) Panel (a) shows the refinancing rates by income quintile, calculated using pooled data from seven surveys conducted between 2004 and 2022. When compared to the Freddie Mac data, the SCF data similarly reveals that lower-income households exhibit a lower propensity to refinance. However, the SCF data overall shows higher refinancing rates, likely

due to differences in data coverage, as will be discussed later.

Conversely, Panel (b) displays refinancing rates divided into quintiles based on the leverage (loan balance to income) ratio as per [Chen et al. \(2020\)](#). Interestingly, this presents a contrasting pattern: the SCF data indicates higher refinancing activity as the leverage ratio increases, whereas the Freddie Mac data shows a decrease in refinancing propensity.

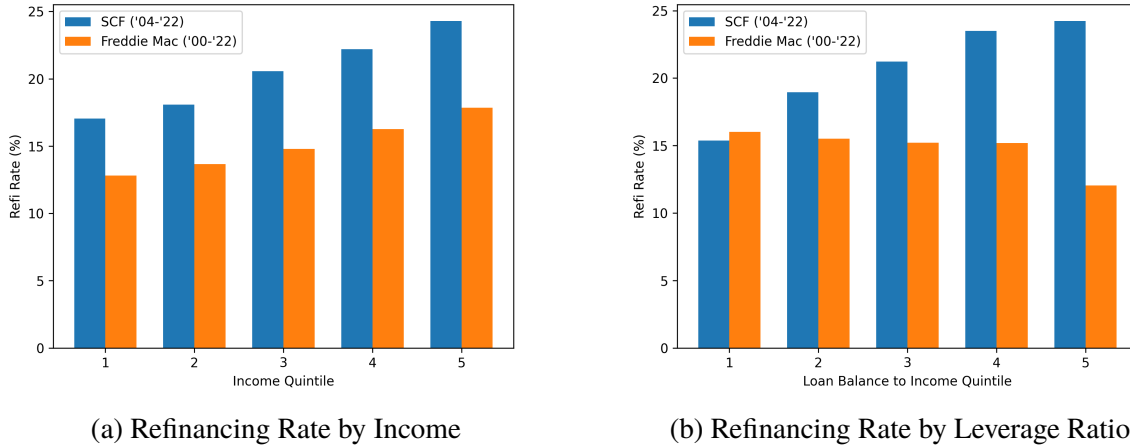


Figure B.7: Refinancing Propensity by Income Quintile and Leverage Ratio

The divergence in these results can be attributed to two main factors. First, the nature of the datasets differs significantly. The SCF is a survey-based triennial dataset that uses current household income, whereas the Freddie Mac data is an administrative panel dataset based on the borrower's income at the time of loan origination. Consequently, differences in the calculation of the loan-to-income ratio, due to variations between household and individual income and current versus past income, complicate direct comparisons.

More importantly, the scope of households covered by each dataset appears to contribute to these contrasting results. As shown in [Figure B.8](#), the types of mortgages in the U.S. are broadly categorized into conventional and non-conventional mortgages. Conventional mortgages are further divided into conforming and jumbo (non-conforming) loans. Conforming loans meet the guidelines set by the Federal Housing Finance Agency (FHFA), including loan limits and credit requirements, whereas jumbo loans exceed these limits. Conforming loans are mostly acquired in the secondary market by government-sponsored enterprises (GSEs) like Fannie

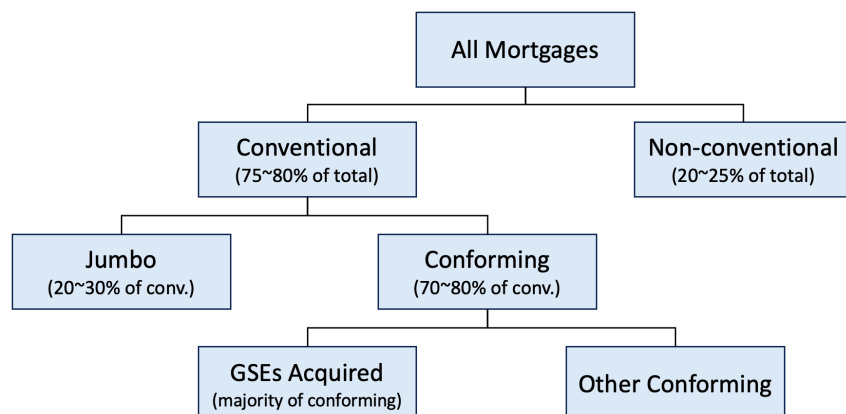


Figure B.8: Mortgage Types in the U.S.

Notes: Market shares of each mortgage type vary over time, and the numbers provided are approximate, referencing the National Mortgage Database (NMDb), web searches.

Mae and Freddie Mac. The Freddie Mac data that I used primarily represents about 70% of conventional loans, accounting for approximately 60% of all loans.

However, the loans not covered by the Freddie Mac data, particularly the jumbo loans, which constitute about 30% of conventional loans, seem to be influencing the results. Jumbo loans, exceeding conforming loan limits, are predominantly held by high-income, wealthy individuals. Since the SCF samples all households, including jumbo loan holders, it exhibits significantly higher income levels, even considering household versus borrower income as shown in [Table B.10](#).

Table B.10: Freddie Mac (Borrower) and SCF (Household) Income by Leverage Ratio

Loan-to-income Quintile	Median Income (\$)		Mean Income (\$)	
	Freddie Mac	SCF	Freddie Mac	SCF
1	53,143	356,204	68,713	1,790,221
2	41,095	161,175	47,831	366,883
3	35,438	119,000	40,494	189,615
4	31,529	95,000	35,493	142,475
5	28,984	58,396	31,971	83,983

Notes: It is important to note that the SCF uses current household income, while Freddie Mac uses the borrower's individual income at the time of loan origination. The statistics are based on the SCF 2004-2022 triannual public data by pooling it together, and Freddie Mac used a sample based on loans originated from 2000 to 2022.

Thus, assuming comparability despite the inherent differences in data characteristics, the sample including all households shows increased refinancing with higher leverage. In contrast, narrowing the analysis to middle and lower-income households reveals an opposite and intriguing pattern. Highly leveraged households might have a high demand for cash-out refinancing due to idiosyncratic shocks, but those with higher absolute incomes might experience fewer frictions related to low income, such as liquidity constraints for closing costs or financial illiteracy, which affect refinancing decisions.

Regarding policy relevance, which dataset is more relevant? If the limitations of survey data is disregarded, the SCF offers a more comprehensive coverage. However, if monetary policy focuses on relatively liquidity-constrained, high-MPC middle and lower-income households, the subset I used would be more significant for policymakers. Specifically, frictions unique to lower-income households can disrupt the transmission channels of monetary policy, making the refinancing behavior of the wealthy less pertinent. Comparing refinancing propensity using consistent income standards across different data scopes could be an interesting area for further research.

B.4 Different Specifications of Refinancing Response

Apart from [Equation 5](#), there may be other specifications to measure regional refinancing responses. Therefore, in this section, we verify robustness by using alternative methods.

$$\rho_{t+h}^{r,j} = \frac{x_t^{r,j} + \dots + x_{t+h}^{r,j}}{y_{t-1}^{r,j}} \quad (8)$$

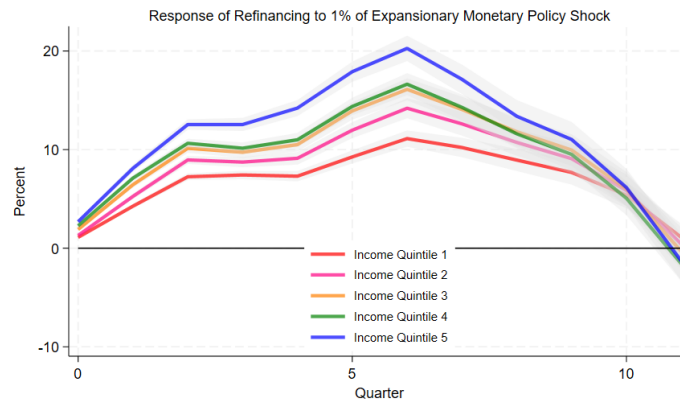
$$\rho_{t+h}^{r,j} = \frac{x_t^{r,j}}{y_t^{r,j}} + \dots + \frac{x_{t+h}^{r,j}}{y_{t+h}^{r,j}} \quad (9)$$

Again, $x_t^{r,j}$ is the number of refinancing loans by income quintile j in region r in quarter t , $y_t^{r,j}$ is the number of all outstanding loans, and h is the analysis time horizon.

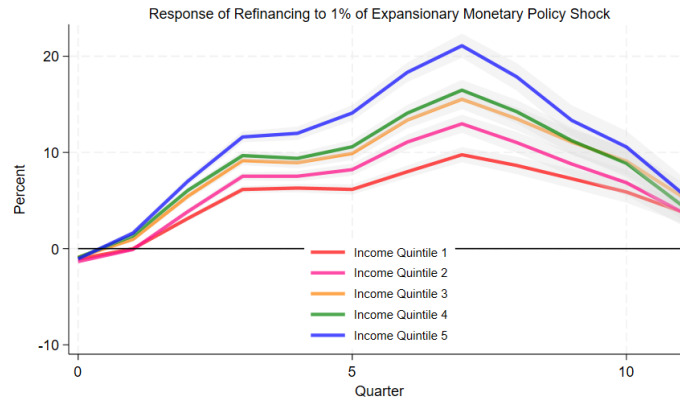
[Equation 8](#) fixes the denominator to the period before the monetary shock arrives. This approach reduces the distortion caused by underestimating the refinancing share due to an

increase in the total number of outstanding loans prompted by home purchases in that region. On the other hand, if the horizon extends and there are loans that refinance multiple times, it may overestimate the response magnitude. Equation 9 is the cumulative sum of the refinancing ratios for each quarter. If the total number of outstanding mortgages does not change significantly, it is expected to show a ratio similar to Equation 8.

Both specifications consistently demonstrate refinancing inequality. Although the timing of the peak differs by only one quarter, both indicate that high-income households refinance significantly more than low-income households.



(a) Equation 8



(b) Equation 9

Figure B.9: Refinancing Response to 1% Interest Rate Cut by Income Quintile

Notes: Panel (a) shows the cumulative refinancing response by income quintile to 1% interest rate falls using Equation 9. The dependent variable is the cumulative proportion of loans refinanced in each region and income group as described in Equation 5. Regions are 908 three-digit ZIP code, and quarterly data from 2004 to 2022 was used

C Appendix: Identification of In-the-money Loans

As described in the text, an in-the-money loan refers to a situation where the difference between the old and new interest rates after refinancing exceeds a certain threshold. This threshold represents the fixed costs associated with refinancing and option value.

$$\text{In-the-money if } \underbrace{(\text{Interest Rate}_i^{old} - \text{Potential Refi Rate}_{i,t}^{new}) - \text{Threshold}_{i,t}}_{\equiv \text{Rate Incentive}} > 0$$

(i and t denote loan and time respectively)

Agarwal et al. (2013) has proposed the following tractable closed-form solution for the threshold value.

$$\begin{aligned} \text{Threshold} &= \frac{1}{\psi} [\phi + W(-\exp(-\phi))] \\ \psi &= \sqrt{\frac{2(\rho + \lambda)}{\sigma}} \\ \phi &= 1 + \psi(\rho + \lambda) \frac{\kappa(M)/M}{(1 - \tau)} \end{aligned}$$

Here, $W(\cdot)$ is the Lambert W-function, ρ is the real discount rate, λ is the expected real rate of exogenous mortgage repayment, σ is the standard deviation of the mortgage rate, $\kappa(M)/M$ is the ratio of the tax-adjusted refinancing cost and the remaining mortgage value, and τ is the marginal tax rate. The values of the parameters suggested by Agarwal et al., 2013 are $\sigma = 0.0109$, $\tau = 0.28$, $\rho = 0.05$.

$\kappa(M)$ is the cost entailed in refinancing, which is defined by:

$$\kappa(M) = F + fM \left[1 - \frac{\tau}{\theta + \rho + \pi} \left\{ \frac{1 - \exp(-(\theta + \rho + \pi)N)}{N} \frac{\rho + \pi}{\theta + \rho + \pi} + \theta \right\} \right]$$

F is the fixed cost of refinance, f is the points divided by 100, τ is the marginal tax rate, θ is the expected arrival rate of a full deductibility event, such as moving and refinancing. Using

the parameter suggested by the paper $F = 2000$, $f = 0.01$, $\theta = \mu + 0.1 = 0.2$, the cost can be approximated as follows.

$$\kappa(M) = 2000 + 0.007905M$$

Lastly, Lambda is defined as the expected rate of decline in the real principal of the mortgage for reasons other than rate-reducing refinancing, and is defined as:

$$\lambda = \mu + \frac{i^{old}}{\exp(i^{old}\Gamma) - 1} + \pi,$$

Γ is the remaining life of the existing mortgage in years, i^{old} is the current (old) mortgage interest rate for existing loan, μ is the hazard of relocation, and π is the inflation rate. The parameter values used are $\mu = 0.1$ and $\pi = 0.03$, following the paper.

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