Heterogeneity in Mortgage Refinancing

Julia Wu

David Berger, Faculty Advisor
Michelle Connolly, Faculty Advisor

Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
2022

Acknowledgements

I would like to thank Professor David Berger, whose mentorship and support extended far beyond the required. I am also grateful to Professor Michelle Connolly and my peers in Econ 495 and 496 for helpful comments and encouragement. Finally, I would like to thank the Duke Economics department for supporting my research through the Davies Fellowship, Jennifer Sider, Dan Berry, Sophia Perry from the Duke Federal Credit Union, and Stephen Sample and Tom Milledge for their help in making this project possible.

Abstract

Many households who would benefit from and are eligible to refinance their mortgages fail to do so. A recent literature has demonstrated a significant degree of heterogeneity in the propensity to refinance across various dimensions, yet much heterogeneity is left unexplained. In this paper, I use a clustering regression to characterize heterogeneity in mortgage refinancing by estimating the distribution of propensities to refinance. A key novelty to my approach is that I do so without relying on borrower characteristics, allowing me to recover the full degree of heterogeneity, rather than simply the extent to which the propensity to refinance varies with a given observable. I then explore the role of both observed and unobserved heterogeneity in group placement by regressing group estimates on a set of demographic characteristics. As a complement to my analysis, I provide evidence from a novel dataset of detailed information on borrower perspectives on mortgage refinancing to paint a more nuanced picture of how household characteristics and behavioral mechanisms play into the decision to refinance. I find a significant degree of heterogeneity in both the average and marginal propensity to refinance across households. While observables such as education, race and income do significantly correlate with group heterogeneity, it is clear that much heterogeneity may still be attributed to the presence of unobservable characteristics.

JEL Codes: D9, E52, G21

Keywords: Refinance, Mortgages, Clustering, Heterogeneity

1 Introduction

The importance of mortgage refinancing as a channel for monetary policy to affect households has been well-documented, yet a growing body of evidence shows that many households fail to refinance despite significant monetary benefits. Furthermore, a nascent literature demonstrates a significant degree of heterogeneity in the propensity to refinance across various dimensions; race, employment status, and the level to which borrowers are credit-constrained have all been identified as factors, yet much heterogeneity is left unexplained.

Policy actions by the Fed have the potential to greatly affect household consumption through housing markets, given that housing is the largest and most widely held asset for US homeowners, with 79 million homeowners owning roughly $36 trillion of real estate[1]. Therefore, a more nuanced understanding of how monetary policy affects the housing market, thereby affecting consumption, is crucial in creating well-tailored economic policy. In practice, the effects of such policy depend on a number of factors, including a household's ability to actually take advantage of lower mortgage rates by refinancing. In the United States, the most popular mortgage product by far is the 30-year fixed-rate mortgage, comprising over 90% of the US mortgage market. FRMs charge a set interest rate over the lifetime of the loan and require a fixed monthly payment, making housing-cost budgeting fairly hands-off for borrowers. In addition to FRMs, many other types of mortgage loans exist; in particular, adjustable-rate mortgages (ARMs), which are characterized by shorter loan terms and an interest rate schedule that remains fixed for a period of 3-7 years before adjusting to the current market rate. 30-year FRMs are appealing to the risk-averse borrower for various reasons, namely that payments are relatively low, due to long loan terms, and that they protect against rising interest rates. To take advantage of lower interest rates, households with FRMs must refinance their mortgages, replacing existing debt with new terms, lower interest rates, and/or lower monthly payments.

Despite significant ostensible benefits, evidence suggests that households are not refinancing as often as expected. One obvious barrier is that a household may fail to qualify for a refinance due to institutional constraints such as a low credit score, high loan-to-value ratio (LTV), or liquidity constraints. Additionally, however, there exist a variety of behavioral factors that may inhibit a borrower's desire to refinance: for example, lack of information, distrust in financial institutions, and peer effects. While other papers have attempted to quantify the impact of certain observables on borrowers' ability and willingness to refinance, the difficulty of capturing behavioral mechanisms through borrower and loan-characteristic data has made a complete understanding of the refinance decision-making process largely elusive.

Previous literature on the underlying mechanisms of suboptimal refinancing has typically taken the approach of choosing a key observable to investigate prior to analysis, then estimating how the propensity to refinance varies with the chosen observable. Because this approach requires the researcher to assume the source of heterogeneity *ex ante*, it

[1] Amromin, Bhutta, and Keys 2020. And https://www.zillow.com/research/zillow-total-housing-value-2020-28704/

does not recover the unconditional distribution of refinance propensities, but rather measures the correlation between refinancing and a given observable. It is also unable to capture heterogeneity due to unobservable characteristics. This paper seeks to close this gap in understanding using two methods. First, I apply a clustering algorithm to a large set of loan-level data on US mortgages to obtain group-specific estimates of the average and marginal propensity to refinance. Importantly, I cluster observations into groups based solely on the heterogeneous propensities to refinance themselves, rather than observable characteristics. Once group-specific estimates are obtained, I then regress group membership on a wide array of borrower characteristics to uncover which observables are significant drivers of group heterogeneity. This approach allows me to remain agnostic on possible relationships between observables and the heterogeneity until after observations are clustered, offering the dual advantages of (1) uncovering both latent and observable characteristics, and (2) estimating joint relationships between observables without the loss of statistical power typically associated with split-sample regressions. My results indicate that there is a large degree of heterogeneity in both the average and marginal propensity to refinance, and that while education, income, race and employment status are all significant predictors of refinance behavior, there remains considerable variation due to unobserved characteristics.

Second, I survey members of a local financial institution to better understand the behavioral mechanisms involved in the refinance decision-making process. Given the degree of unexplained heterogeneity in the propensity to refinance, it is fair to assume that a significant portion can be attributed to latent factors such as idiosyncratic borrower preferences or other behavioral mechanisms. However, since it is typically difficult to capture such characteristics through conventional data, current literature has lacked the means to do little more than make educated guesses as to the true source of this heterogeneity. I attempt to fill this data gap by directly surveying participants about their familiarity with and exposure to mortgage refinancing, as well as their own mortgage refinancing decisions. I find that many households attribute their lack of refinancing to institutional constraints such as low credit scores and extra fees, with effects being more pronounced in Black and low income borrowers. Given these results, I find that information asymmetry is a key mechanism through which suboptimal refinancing occurs.

The rest of this paper proceeds as follows. Section 2 summarizes related literature. In section 3, I outline my main empirical approach, and in section 4 I describe the data. In section 5, I describe results and provide micro-level evidence from a survey on borrower perspectives on refinancing. Section 6 concludes.

2 Literature Review

A large literature provides motivation for the importance of mortgage markets in effective monetary policy transmission. Beraja et. al (2019) and Berger et. al (2021) provide insight into the role that time-varying refinancing incentives, such as housing equity and interest rates, play on the effects of monetary policy. Both find that incentive variation yields varying rates of refinance and, in turn, variation in household consumption, demonstrating a direct link between refinance rates and household spending responses.

My work builds on a sizeable literature on suboptimal mortgage refinancing and, in particular, the household's decision-making process. Many households fail to refinance even when the option is significantly "in the money" and there are minimal structural barriers, losing an estimated $11,500 on average in present value over the lifetime of the loan (Keys, D. G. Pope, and J. C. Pope 2016; Green and LaCour-Little 2000). Amongst those who do refinance, many still do so at either a suboptimal rate or suboptimal time, suggesting that borrowers are missing out on substantial monetary benefits either because they are unable to correctly evaluate when a refinance is optimal or because they have unobserved preferences that make an ostensibly beneficial refinance suboptimal (Agarwal, Rosen, and Yao 2015; Agarwal, Driscoll, and Laibson 2013). Furthermore, the propensity to refinance is not homogeneous across households; many have documented differential behavior by demographic group. For example, Defusco and Mondragon (2020) find that imposing employment and equity restrictions significantly lowers refinancing rates, implying that the unemployed and liquidity-constrained have a high latent demand for refinancing. Gerardi, Willen and Zhang (2020) analyze prepayment rates by race and find significant differences in across racial and ethnic groups, with Black and Hispanic white borrowers having close to 50 percent lower prepayment rates than their non-Hispanic white counterparts, even after controlling for income, credit score and equity[2].

This paper also relates to a literature on estimating heterogeneity in household preferences. Bonhomme and Manresa (2015) and Sarafidis and Weber (2015) both develop clustering estimators to estimate heterogeneity in panel data, while Lewis, Melcangi and Pilossoph (2021) do so for the cross-sectional setting. These estimators can be applied to different empirical settings to obtain group-specific measures, allowing the researcher to obtain a distribution of heterogeneous estimates. For example, Lewis et. al (2021) use a similar clustering estimator to recover the distribution of marginal propensities to consume out of the 2008 Economic Stimulus Act. Heiss et. al (2021) exploit preference heterogeneity to develop a panel data model of different types of inertia in consumer health-plan choice. They find that allowing for heterogeneity is crucial in creating accurate simulations of consumer inertia.

Finally, I contribute to a literature on survey usage as a means of recovering behavioral data. One of the key challenges of identifying behavioral mechanisms is that many behavioral characteristics are typically unobserved, making them difficult to measure through conventional data. Ameriks et. al (2020) employ an identification strategy that utilizes survey questions to distinguish between supply and demand-side forces affecting labor market participation, while Fuster, Kaplan and Zafar (2018) and Jappelli and Pistaferri (2014) use survey questions to measure heterogeneity in the marginal propensity to consume.

This paper makes three important contributions to the literature. First, I take a novel approach to the task

[2]Prepayment includes cash-out and no cash-out refinances, as well as moving and any other reasons a household may pay off their mortgage early.

of estimating refinance heterogeneity, allowing me to recover the full, unconditional distribution of propensities to refinance. Importantly, I am able to distinguish between refinance and prepayment, whereas many previous papers attempting to document suboptimal refinancing can only observe prepayment. Second, I successfully identify a wide array of statistically significant observable predictors, both individually and jointly, without loss of statistical power. Third, I introduce a novel dataset of borrower perspectives on mortgage refinancing to the literature and investigate behavioral mechanisms behind the decision to refinance that are typically unobserved.

3 Empirical Specification

To estimate the propensity to refinance and how it differs across households, I utilize detailed loan-level mortgage data to look at how the marginal propensity to refinance (henceforth MPR) changes as a function of a household's interest rate gap, defined as the difference between a household's mortgage rate and the prevailing market rate at any given time. A negative rate gap indicates that a household's current interest rate is higher than the market rate, meaning that, generally speaking, they could take advantage of lower interest rates by refinancing. Because mortgage rates at origination are similar across a given year cohort, I limit my analysis to origination-year cohorts.

A household's propensity to refinance may be a function of many different factors, including observable characteristics, such as income level and the amount of home equity held, and unobservable characteristics, including perceived benefit and intrinsic motivation. These characteristics are likely to vary across different demographic groups, so it is naïve to assume a homogeneous propensity to refinance across all households.

To estimate heterogeneous propensities to refinance, households must be clustered into groups. Prior literature has tended to group observations based on observable characteristics, but such an approach requires that one take a stance on the determinants of the refinancing decision *a priori*. Doing so may obscure other relevant observed or unobserved characteristics, the full extent of heterogeneity, or both. In contrast, I employ a method to estimate the distribution of average propensities to consume (APR) and MPRs where observations are clustered on the basis of the heterogeneous MPRs themselves, rather than observables, along with other group-specific parameters. Because this clustering approach does not depend on the presence of observable characteristics, I am able to examine grouped patterns in both observed *and* unobserved characteristics by examining the correlates of the heterogeneous estimates *ex post*.

3.1 Clustering Estimator

Homogeneous Case

I first present the homogeneous case to build intuition for later generalizations. Consider the following specification:

$$P(refi)_{it} = \beta \mathbf{X}_{it} + \gamma R_{it} + \alpha + \epsilon_{it}, \qquad (1)$$
$$i = 1, ..., N; t = 1, ..., T$$

where $P(refi)_{it}$ is the average propensity to refinance for household i in time t, and $\mathbf{X}_{it}$ is a vector of basic controls including location and monthly fixed effects, time left on the loan, outstanding loan balance and equity. R_{it} is the independent variable of interest, which denotes the interest rate gap for each household in time t. γ can then be interpreted as the impact of a unit change in the interest rate gap on the propensity to refinance, i.e. the MPR.

Clustering

When the researcher has information about group membership and the true number of groups G, the task of finding heterogeneous estimates simply reduces to a series of split-sample panel regressions. However, this is often not the case in practice, and while it may be intuitively simple to think of a set of characteristics that may influence such heterogeneity, we are still left with the question of how many true clusters exist and how exactly to choose the correct partition of observations.

There are many different ways to choose the optimal number of groups. In informal settings, one may choose the "elbow" method, in which the researcher calculates and graphs the RSS for each number of clusters and chooses the number of clusters that occurs at the graph's kink. Other methods include the Bayesian Information Criterion (used by Lewis et. al (2021)) and the gap statistic (Tibshirani et. al (2001)).

Researchers make use of many different clustering algorithms, with perhaps the most well-known being the K-means algorithm, which clusters observations into groups based on the distance from an observation and the center of the cluster. In this paper, I employ the clustering method developed in Sarafidis and Weber (2015). To determine the number of groups G, the authors make use of the following model information criterion:

$$MIC = Nlog(\frac{RSS}{NT}) + G\theta_n \qquad (2)$$

where RSS is the residual sum of squares and θ_n is a sequence of constants whose size depends on N. In this paper, I use

$$\theta_n = 1/3ln\sqrt{N} + 2/3\sqrt{N}, \tag{3}$$

which the authors find to perform well under simulated data, but θ_n can take any real-valued argument (other common values include $\sqrt{N}$ and ln(N)). The optimal number of groups is obtained by minimizing the MIC.

To partition observations into G groups, the clustering algorithm begins by choosing a random partition of the data based on the standard normal distribution. It then iterates through each individual in the data (in this case, each loan), assigning the individual to the cluster that minimizes the overall RSS across all groups.

Heterogeneous Case

Accurately characterizing the distribution of propensities to refinance requires some understanding of the ways in which household refinance behavior may vary. I identify three distinct possibilities:

On one hand, it may be the case that while certain households are on average more likely to refinance than others, all households share similar behavior on the margin. That is, a household A may pay more attention to interest rates and thus be more likely to refinance on average than household B, but the two may share a similar sensitivity to a unit change in their respective rate gaps. We modify equation (1) to obtain

$$\begin{gathered} P(refi)_{it} = \beta \mathbf{X}_{it} + \gamma R_{it} + \sum_{g=1}^{G} \mathbf{1}[i,t \in g]\alpha_g + \epsilon_{it}, \\ i = 1,...,N; t = 1,...,T; g = 1,...,G \end{gathered} \tag{4}$$

where $\sum_{g=1}^{G} \mathbf{1}[i,t \in g]$ is an indicator for group membership, taking a value of 1 if a household i in period t belongs in group $g = 1,...,G$ and $\alpha_g = (\alpha_1,...,\alpha_G)'$ represents a vector of group-specific intercepts. As before, γ is the marginal effect of a unit change in the rate gap on the propensity to refinance. Notice that γ and β remain constant across all households.

Alternatively, it may be the case that all households share a similar average propensity to refinance but demonstrate different marginal behaviors. We again modify equation (1) to obtain

$$\begin{gathered} P(refi)_{it} = \beta \mathbf{X}_{it} + \sum_{g=1}^{G} \mathbf{1}[i,t \in g]\gamma_g R_{it} + \alpha + \epsilon_{it}, \\ i = 1,...,N; t = 1,...,T; g = 1,...,G \end{gathered} \tag{5}$$

where α is once again common across all households, but $\gamma_g = (\gamma_1,...\gamma_G)'$ is allowed to be heterogeneous across groups.

Of course, it is also possible that households differ in both average and marginal behavior. We see this in equation (6)

$$
\begin{aligned}
P(refi)_{it} = \sum_{g=1}^{G} \mathbf{1}[i, t \in g](\beta_g \mathbf{X}_{it} + \gamma_g R_{it} + \alpha_g) + \epsilon_{it}, \\
i = 1, ..., N; t = 1, ..., T; g = 1, ..., G
\end{aligned} \tag{6}
$$

where $\alpha_g = (\alpha_1, ..., \alpha_G)'$ and $\gamma_g = (\gamma_1, ..., \gamma_G)'$ are heterogeneous across groups.

Correlating Observables and Clustering Regressions

Once group-specific estimates of the APR and MPR are recovered, I am able to investigate the correlation between group membership and various loan and borrower characteristics using a multinomial logit regression of the form

$$P(i \in g = 1, ..., G) = \omega + \phi' C_{it} + \mu_{it}, \tag{7}$$

where $P(i \in g = 1, ..., G)$ is the probability that loan i is in group g and C_{it} is a vector of observables including borrower characteristics such as race, education and income level. In addition to recovering the full degree of heterogeneity, this approach has the benefit of being able to jointly observe relationships between loan and borrower characteristics without loss of statistical power.

4 Data

4.1 Loan-Level Data

For my primary analysis, data come from Corelogic Solutions. The Corelogic Loan-Level Market Analytics data are collected from the nation's largest mortgage servicers and contain detailed information on loan-level characteristics such as origination date, zip-code, LTV, interest rates (both current and at origination), and payoff reason, as well as full payment history (late payments, etc). The Corelogic data do not include many borrower demographics, so to supplement these data, I merge in Census data on household characteristics at the zip-code level, including median household income, education, age, employment status and race.

To construct the sample, I begin with a random sample of all first-lien, single-family, 30-year fixed rate, owner-occupied mortgages. I then exclude any loans with missing interest rate, LTV and FICO score at origination, or payoff reason. For loans with missing equity, I estimate equity for each loan-month using the zipcode-level Federal Housing

Finance Agency House Price Index. The resulting analysis sample contains 2,434 loans and 162,110 loan-month observations.

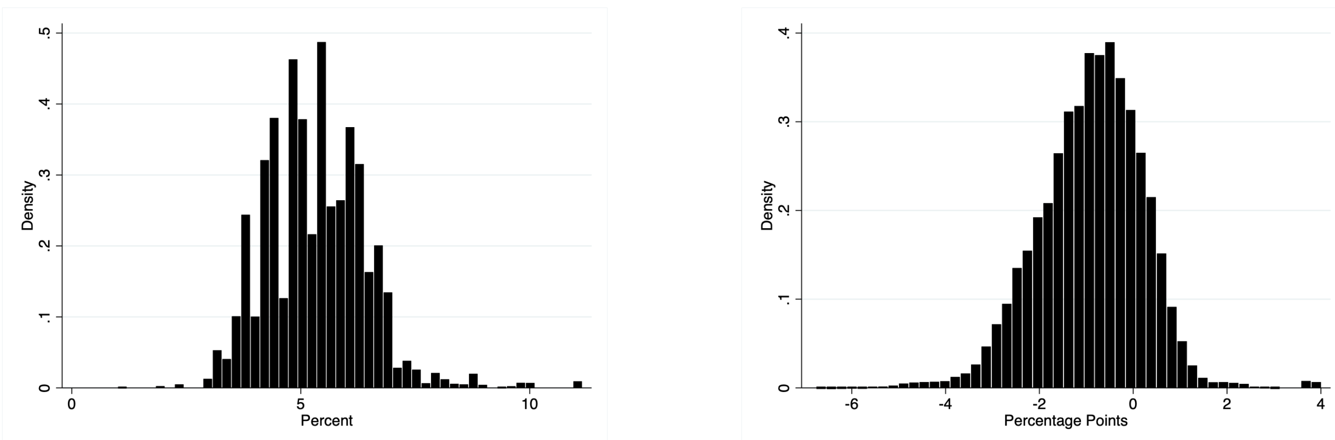
Table 1 reports summary statistics. Column (1) summarizes all loans, while column (2) is restricted to all loans that are first-lien, single-family, 30-year fixed-rate, and owner-occupied that also have non-missing interest rate, LTV, FICO score at origination and payoff reason (for brevity, I refer to these as ”restricted loans” for the remainder of the paper). Summary statistics in Panel A are reported at the loan level and are measured at the time of origination. Summary statistics in Panel B are reported at the loan-month level and are measured for every month that a loan is represented in the data. We see that restricted loans are slightly younger and have slightly lower outstanding balances compared to the full sample, despite sharing similar loan amounts at origination. However, columns (1) and (2) show similar FICO scores and interest rates at origination. The average rate gap in the full sample is -0.71 percentage points and -0.95 in the restricted sample, indicating that, conditional on meeting qualifications, loans in both the full and restricted samples would benefit from refinancing. We also see this difference reflected in the percent of loans that have refinanced; 4.02% of loans in the full sample refinance, while 11.04% of loans in the restricted sample do.

Table 1: Corelogic Summary Statistics

	All Loans (1)	Restricted (2)
Panel A: Loan characteristics at origination		
Loan Amount ($1000's)	200.17	201.86
	(217.13)	(117.89)
FICO Score	717.59	711.61
	(70.98)	(67.36)
Interest Rate	5.16	5.30
	(1.65)	(1.21)
LTV	77.38	82.98
	(20.48)	(18.33)
N	26,659	2,434
Panel B: Loan-month characteristics		
Current Balance ($1000's)	154.08	139.98
	(211.97)	(125.82)
Loan Age (Months)	66.27	56.57
	(53.44)	(43.45)
Percent Refi	4.02	11.04
	(19.64)	(31.34)
Rate Gap	-0.71	-0.95
	(0.27)	(1.22)
Equity ($1000's)	303.74	251.08
	(577.27)	(371.10)
N	1,747,942	162,110

Note: A negative rate gap indicates that a loan's current interest rate is higher than the market rate. Standard deviations reported in parentheses.

Particularly relevant to this analysis is the degree of variation in interest rates across homeowners. Figure 1a illustrates the distribution of interest rates at origination, while Figure 1b shows the distribution of the rate gap. While there is significant variation across loans, it is clear that most have the potential for significant savings, with some loans having interest rates as high as 6% over the market rate. Section 1 of the appendix presents the rate gap distribution every two years from 2006-2018. Prior to the Great Recession, we see much less variance and a higher proportion of positive rate gaps. Starting in 2008, we see a sudden increase in both the spread and the proportion of negative rate gaps that remains through most of the 2010s. This may be due in part to revised regulations as a result of the housing crisis. In any case, these figures help demonstrate the scope of failure to refinance and the importance of understanding why households are not refinancing when it is financially beneficial to do so.



(a) At Origination

(b) Rate Gap

Figure 1: Distribution of Interest Rates

5 Results

I apply the clustering approach to panel data on loan performance over time. Using the method described in the previous section, I find that the optimal number of groups G is 8. In addition to baseline restrictions, I also drop all loan-month observations older than 10 years (from origination), as well as any loans that prepaid within 10 years but were not refinances, for a final sample size of 1,342 loans, 82,403 loan-months and an average panel length of 61.4 loan-months. Table 2 reports group-specific estimates of the APR and MPR. Both OLS estimates and odds ratios are reported for the MPR.

I find that households display a considerable degree of heterogeneity in both the APR and MPR, with estimates ranging from 0.073 to 0.386 and -0.046 to 0.269, respectively. In particular, we see four types of households emerge: households with high average propensities to refinance (APRs) and MPRs, households with low APRs and MPRs, as well as households with low APRs and high MPRs and those with high APRs and low MPRs [3]. On average, households display an average propensity to refinance of 0.189 and an MPR of 0.027. In other words, for a one percentage-point decrease in the rate gap, a household's marginal propensity to refinance increases by 2.7 percentage points [4]. From the odds ratios, we get a sense of how much a unit change in the rate gap changes the odds of refinancing across groups. As expected, groups with greater MPRs also demonstrate a greater change in the odds of refinancing. For example, households in group 4 exhibit an MPR of 0.269 and an odds ratio of 0.306, indicating that, for a unit *increase* in the rate gap, the odds of refinancing decrease to 0.306 of the baseline. Although estimates of the MPR across groups vary in magnitude, the vast majority demonstrate positive MPRs, indicating that households become more likely to refinance the higher their interest rate is above the market rate. These findings are consistent with the idea that the propensity to refinance increases as the option to refinance gets more "in the money." Importantly, while the average APR across groups is similar to the homogeneous specification (0.190), the average MPR differs significantly in magnitude from the homogeneous estimate (0.047). From a policy perspective, this difference in magnitude implies that policymakers may be significantly overestimating households' true sensitivity to interest rate changes.

5.1 What Drives Refinance Heterogeneity?

In contrast to existing literature, my approach attempts to characterize the distribution of refinance propensities without relying on observable characteristics. Instead, I recover potential relationships with observables *ex post*, allowing the data to "speak for itself," to understand how well correlates align with standard views on the determinants of refinancing. This approach offers the advantage of greater statistical power, since relationships can be

[3] I categorize an estimate as Low if it is in the bottom half of estimates across groups.

[4] Recall that the rate gap is defined as `current market rate - loan's interest rate`, so a negative rate gap indicates that a loan's current interest rate is greater than the prevailing market rate. Thus, I use *increase* and *decrease* to mean a move along the real number line in either the positive or negative direction, *not* a change in magnitude.

Table 2: Refinance Heterogeneity: Logit and OLS Estimates

	Homogeneous (1)	Group 1 (2)	Group 2 (3)	Group 3 (4)	Group 4 (5)	Group 5 (6)	Group 6 (7)	Group 7 (8)	Group 8 (9)
APR	0.190***	0.250***	0.097***	0.307***	0.386***	0.262***	0.319***	0.073***	0.264***
	(0.001)	(0.004)	(0.003)	(0.006)	(0.018)	(0.004)	(0.004)	(0.002)	(0.006)
MPR									
OLS	0.047***	0.075***	-0.037***	-0.046***	0.269***	0.042***	0.088***	0.000***	0.083**
	(0.001)	(0.003)	(0.003)	(0.005)	(0.010)	(0.004)	(0.004)	(0.003)	(0.004)
Odds Ratios	0.957***	0.889***	1.113***	0.924	0.306***	0.986***	0.762***	1.423***	0.824***
	(0.009)	(0.023)	(0.035)	(0.044)	(0.124)	(0.033)	(0.034)	(0.030)	(0.037)
Type (APR, MPR)		Low, High	Low, Low	High, Low	High, High	Low, Low	High, High	Low, Low	High, High

Note: Standard errors reported in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

jointly estimated without having to cut the data into smaller partitions, as well as recovering the true distribution, rather than observing a change in behavior in response to a given observable, as others have previously done.

Demographic data come from the 2001-2019 American Community Surveys (ACS). The ACS is a nationally representative survey containing detailed information on education, housing, demographic and social characteristics of the population. While I am able to track variation in observables over time, I only observe demographic characteristics at the zipcode level. Thus, to an extent, such observables are more accurately interpreted as a neighborhood or peer effect.

First, I examine the relationships between individual observables and group placement. Table 3 shows the average value (unless otherwise specified) for each observable across groups. Again, we see considerable heterogeneity in observables from group to group. In Section 2 of the appendix, I show that these observables are jointly significant. Consistent with the literature, households in highly educated areas with good credit and high rates of employment, such as those in Group 4, have high APRs and MPRs, while households who exhibit low APRs and MPRs tend to live in areas with fewer college-educated residents and lower home values. However, we also see that some households who would be expected to have high propensities to refinance based on observable characteristics do not, while others who would not be expected to have high propensities to refinance, in fact, do. For example, Group 8 shows the lowest home value, household income, fraction employed and fraction college-educated, yet demonstrates both high average and marginal propensity to refinance.

Of particular interest are those who exhibit high APRs and low MPRs or low APRs and high MPRs. Are we able to distinguish any patterns that explain why some households are generally not inclined to refinance often but demonstrate a high sensitivity to changes in the interest rate? Why would households who generally refinance often then have a low sensitivity to changing interest rates? I identify two groups who exhibit this behavior: Groups 1 and 3. Households in Group 1 are of type Low, High (APR: 0.250, MPR: 0.075) and have a 23% chance of being college-educated and a 48% chance of being employed, falling below the median across groups for both measures. Households in Group 4 are of type High, Low (APR: 0.307, MPR: -0.046) and exhibit high credit scores, household incomes and employment rates. Both groups exhibit observable traits that are consistent with their respective APR types, suggesting that perhaps observable traits drive heterogeneity in a household's overall propensity to refinance more so than a household's sensitivity to interest rate changes.

Overall, although many of the given observables are statistically significant drivers of group placement, we do not observe many clear trends in group membership and even see households who appear similar based on observables demonstrate decidedly different refinance propensities. For example, households in Groups 5 and 6 have credit scores within one point of each other and similar rates of college education, but are of type Low, Low and High, High, respectively.

How can we explain the amount of heterogeneity in refinance propensities when we do not observe clear patterns in the given observables and even see markedly different refinance propensities from households who appear similar based on observable traits? It must be the case that much of the heterogeneity we see is attributed either to other observable characteristics that these data do not capture (for example, one might imagine that wealth, in addition to income, may indicate something about a household's propensity to refinance) or to unobservable characteristics. Without this information, it can be difficult to see the full story. To the extent that other observables are relevant but not represented in the data, I cannot distinguish between the impact of unobserved behavioral characteristics and missing observables in explaining the remaining group heterogeneity. However, given that prior literature has been unable to fully explain suboptimal refinancing through observable characteristics, it is likely that a considerable degree of heterogeneity is due to the presence of unobserved behavioral mechanisms. To better understand how these affect the decision the refinance, in the next section I discuss the results of a survey of borrower perspectives on mortgage refinancing.

Table 3: Observables By Group

	Group 1 (1)	Group 2 (2)	Group 3 (3)	Group 4 (4)	Group 5 (5)	Group 6 (6)	Group 7 (7)	Group 8 (8)
Fraction Non-White	*0.267*	0.276	0.341	**0.398**	0.276	0.306	0.286	0.283
	(0.145)	(0.137)	(0.172)	(0.106)	(0.139)	(0.306)	(0.152)	(0.177)
Fraction Black	0.152	*0.134*	0.145	**0.227**	0.157	0.184	0.166	0.193
	(0.127)	(0.103)	(0.129)	(0.140)	(0.133)	(0.158)	(0.134)	(0.160)
Fraction Asian	0.049	0.069	**0.103**	0.093	0.047	0.051	0.050	*0.034*
	(0.053)	(0.066)	(0.104)	(0.060)	(0.030)	(0.033)	(0.048)	(0.022)
Fraction with College Degree	0.230	0.259	0.296	**0.330**	0.233	0.240	0.230	*0.207*
	(0.068)	(0.084)	(0.081)	(0.100)	(0.064)	(0.061)	(0.072)	(0.059)
Fraction Employed	0.480	0.485	**0.504**	0.502	0.481	0.494	0.479	*0.475*
	(0.033)	(0.047)	(0.036)	(0.055)	(0.042)	(0.032)	(0.041)	(0.039)
Median Household Income	66800	72500	**87930**	85000	66000	74790	65000	*59600*
	(15440)	(22651)	(22325)	(28241)	(15658)	(17113)	(19239)	(12629)
Median Home Value	168000	300000	480000	**751000**	210748	290055	177045	*110000*
	(74786)	(272265)	(227309)	(337028)	(71367)	(122931)	(141430)	(35627)
FICO Score at Orig.	709.16	716.34	**743.77**	733.86	719.79	719.44	*696.77*	712.20
	(72.51)	(59.27)	(50.39)	(64.38)	(64.05)	(57.25)	(71.29)	(62.82)
Type (APR, MPR)	Low, High	Low, Low	High, Low	High, High	Low, Low	High, High	Low, Low	High, High

Note: This table presents individual estimates of group-specific averages (unless otherwise specified) across observables. The FICO score at origination is observed at the individual level, while all other observables are observed at the zipcode level. All covariates are observed over time. The highest estimate for each observable across groups is denoted by bold text, and the lowest by italicized text. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

5.2 Refinance Survey

In the previous section, I characterize heterogeneity in the propensity to refinance in two ways and provide estimates of the distribution of the average and marginal propensity to refinance across groups. While these data are useful for quantifying the degree of heterogeneity, we may also benefit from more granular evidence on mechanisms which are typically unobserved in conventional datasets.

In response to this gap in the literature, I designed and conducted a survey to better understand which borrowers choose not to refinance and why. Participants were comprised of members of the Duke Federal Credit Union (DFCU). DFCU serves members of the Duke community, including employees and retirees of Duke University and the Duke University Health System, students and alumni, Duke affiliated organizations (e.g., sports teams), and immediate family members of any of the above parties. DFCU offers a variety of services, including savings and checkings accounts, as well as auto, student, and mortgage loans.

In July of 2021, DFCU distributed an online survey to the approximately 8,000 members with accessible emails, 343 of whom responded in full. The survey asked a series of questions about a respondent's opinions on and familiarity with mortgage refinancing, including how familiar they were with the term and whether they had peers who had refinanced mortgages. The survey also asked about the respondent's own refinance experience; in particular, whether (conditional on having a mortgage) they had ever refinanced a mortgage and why or why not. Respondents were not offered an incentive of any kind for taking the survey, and participation was optional.

Table 4 compares survey participant demographics against the national distribution. Women are significantly overrepresented within the sample, as are Black participants and those with higher degrees. The distribution of household income amongst participants more closely matches the national distribution, but still skews left. Table 5 presents summary statistics. On average, survey respondents held mortgage loans at a significantly higher rate than the national average. Both possession and refinance of mortgages (conditional on holding a mortgage loan) generally increased with education and income; this is consistent with behavioral theories that suggest increased education and income result in increased financial literacy. The lack of representativeness within the survey sample may present some concerns regarding external validity. However, given the lack of data on borrower perspectives on refinancing in the literature, this case study presents a useful baseline for understanding the behavioral underpinnings behind the decision to refinance.

Table 4: Survey Participant Demographics

	National Average	**Survey Participants**
By Gender:		
Male	48.73	25.07
Female	51.27	71.14
Prefer not to say	.	3.79
By Race:		
Black	12.12	30.90
White	74.66	56.56
Asian	4.90	2.04
Other	8.32	4.37
Prefer not to say	.	6.12
By Education:		
High School or Less	53.30	6.46
Some College	22.68	25.81
Bachelor's Degree	12.91	31.38
Master's or Professional Degree	6.52	22.87
Ph.D.	0.84	10.56
Prefer not to say	.	2.93
By Income:		
Less than $40,000	29.08	9.38
$40,000 - $70,000	23.74	26.98
$70,000 - $100,000	16.86	19.93
$100,000 - $150,000	14.63	15.84
More than $150,000	15.69	15.84
Prefer not to say	.	12.02

Note: All statistics are reported as percentages. Nationally representative statistics come from the 2001-2019 ACS data. N=343

Of the 343 participants, approximately 75% indicated that they had refinanced a mortgage at some point. Participants who refinanced were asked to indicate the reasons why they chose to refinance. Results are outlined in Table 6. A lower monthly payment was the most popular reason to refinance by far, with less than half of participants indicating that they refinanced to extract equity from their home or to change their loan terms. Similar results held

Table 5: Refinance Survey Summary Statistics

	Have Mortgage	**Have Refinanced**
Entire Sample	83.82	75.35
National Average	65.40	.
By Gender:		
Male	78.83	73.53
Female	85.54	76.10
By Race:		
Black	74.29	67.11
White	91.15	78.98
Asian	71.43	80.00
Other	75.00	74.07
By Education:		
Bachelor's Degree or Less	81.95	58.82
Master's	87.18	91.18
Ph.D.	91.43	75.00
By Income:		
Less than $40,000	50.00	43.75
$40,000 - $70,000	72.82	63.64
$70,000 - $100,000	85.30	78.95
$100,000 - $150,000	100.00	79.63
More than $150,000	98.15	90.57

Note: All statistics are reported as percentages. N=343 when broken down by race and income.

Table 6: Reasons Why Borrowers Refinanced

	Percent of Participants Who Refinanced
To Lower Monthly Payment	74.77
To Extract Equity	31.31
To Change Loan Terms	26.64

Note: Participants were able to select multiple answers. In addition to these choices, participants were offered an "Other" option, as well as an open-ended response box. I did not receive any other reasons beyond the three listed. N=214

Table 7 reports results for those who chose not to refinance. Participants had the option to select multiple responses, as well as provide additional comments through an open-ended response. Column (1) indicates the percentage of homeowners who selected a particular response out of all homeowners who have never refinanced any mortgage. Columns (2) and (3) repeat the same for white and Black homeowners, respectively, and columns (4) and (5) do so for homeowners with household income below and above the national median. Column (1) demonstrates that within the full sample, low credit scores, extra fees and a lack of perceived benefit emerge as the most common reasons why homeowners chose not to refinance. Black homeowners were also more likely to cite not understanding refinancing and not trusting financial institutions than white homeowners, while low income participants were especially likely to select low credit scores and extra fees. Black and low income participants were both more likely to select effort and time as reasons.

Considering the range of reasons why a household may choose not to refinance, blanket policies intended to increase refinancing are likely to be focusing disproportionately on some groups. The ability to effectively target certain households has particularly important implications for inequality and the racial wealth gap, as Gerardi, Willen and Zhang (2020) find that not only do Black homeowners prepay at significantly lower rates than white homeowners, but that the gap between prepayment rates increased in response to expansionary monetary policies like the Federal Reserve's large-scale asset purchase programs following the Great Recession. In light of these results, it appears that information asymmetry may be at the heart of suboptimal refinancing, particularly for Black and low income participants. For example, many indicated that extra fees associated with the refinancing process were a barrier to refinancing. In most cases, however, borrowers are able to roll any closing costs into their loan balance, effectively decreasing the upfront capital required to refinance. In addition, many participants who said extra fees were cost-prohibitive had household incomes over $100,000, suggesting that a failure to refinance might not truly be due to liquidity constraints. A lack of information is also consistent with behavioral explanations like inertia and ambiguity aversion, in which individuals prefer the known over the unknown despite potential gains. Policymakers may therefore find it worthwhile to focus their efforts on increasing information about the refinancing process and its many available options, rather than directly addressing attributes of the refinance process. Policymakers may also benefit from investing in credit-building programs, as well as community-based programs focused on building trust between borrowers and financial institutions.

Table 7: Reasons Why Borrowers Did Not Refinance

	All Homeowners (1)	White Homeowners (2)	Black Homeowners (3)	Below Median Household Income (4)	Above Median Household Income (5)
My credit score is too low.	28.57	18.92	40.00	39.39	18.92
I can't afford the extra fees.	22.86	18.92	24.00	30.30	16.22
I don't think I would benefit.	22.86	29.73	20.00	24.24	21.62
I don't understand what refinancing is.	12.86	10.81	16.00	24.24	2.70
I don't trust financial institutions.	11.43	5.41	16.00	9.09	13.51
I haven't had my mortgage long enough.	11.43	13.51	12.00	21.21	2.70
It takes too much effort.	8.57	5.41	12.00	12.12	5.41
I am moving soon.	7.14	13.51	0.00	3.03	10.81
It takes too much time.	5.71	2.70	8.00	12.12	0.00
I don't have the proper documents.	5.71	5.41	0.00	3.03	8.11
I don't know my credit score.	4.29	5.41	4.00	3.03	5.41
I am unemployed.	1.43	2.70	0.00	3.03	0.00
N	70	37	25	33	37

Note: Statistics are reported as the percentage of homeowners who *did not* refinance and are sorted highest to lowest according to column (1). Participants were allowed to select multiple answers. Open-ended responses have been edited for clarity. Median household income refers to the national income distribution, not of the sample.

6 Conclusion

In this paper, I apply a clustering approach to detailed loan-level data on US mortgages in order to estimate heterogeneity in the propensity to refinance. I find a considerable degree of heterogeneity in both the APR and MPR, with households on average demonstrating an APR of 0.190 and an MPR of 0.047. This strategy improves upon previous approaches in that it recovers the full degree of heterogeneity, rather than simply estimating how the APR or MPR varies with a given observable. I then examine how observables, both individually and jointly, correlate with different types of refinance behavior. Consistent with prior literature, I find that observables such as education, income, race and employment are significantly correlated with heterogeneity. Because my approach allows me to identify heterogeneous estimates without partitioning the data on borrower observables, I can be sure that such relationships are truly significant and not subject to concerns about statistical power. However, the evidence also demonstrates that many households who appear to be similar based on observable characteristics exhibit considerably different refinance behavior, underscoring the importance of unobserved characteristics in understanding refinance heterogeneity.

As a complement to my analysis, I also conduct a survey on borrower perspectives on refinancing to uncover the behavioral mechanisms underlying the refinance decision. I provide evidence that race and income are two dimensions along which unobserved characteristics vary, and find that information asymmetry may be at the core of why Black and low income households refinance at lower rates.

This paper is subject to certain limitations. Because I do not observe borrower characteristics within the Corelogic data, I must merge in demographic data from the ACS at the zipcode level. Thus, estimates involving observables are subject to a degree of measurement error due to a lack of granularity. Like most surveys, my survey data are also subject to a degree of measurement error and human subjectivity. Because all survey participants are affiliated with Duke University in some way, the sample is likely to be biased and thus participants are unlikely to provide nationally representative responses. Due to data sensitivity restrictions, demographic data are binned, so I am unable to determine an individual's exact age, income or credit score [5].

Overall, these results suggest that the effective transmission of monetary policy through mortgage markets hinges on tailoring policy towards specific subgroups of the population. Furthermore, the degree of heterogeneity exhibited in this paper provides evidence that the success of such policies may depend on their ability to address behavioral factors, like inertia and ambiguity aversion, in addition to traditional observable traits like liquidity constraints. Many have considered mortgage products which combine the benefits of FRMs and ARMs by allowing interest rates to adjust down but not up, protecting against rising interest rates while still allowing households to automatically take advantage of decreasing rates. Others have suggested that a degree of statistical discrimination in

[5] See Section 2.2 of the appendix for survey questions.

the mortgage market may actually help increase refinance rates for underperforming groups, for example by offering the aforementioned products to Black homeowners but not white. More generally, an important area for future research is to explore the implications of heterogeneity in refinance propensities on future policy choices, particularly in regards to the role of unobservables.

References

Agarwal, Sumit, John C. Driscoll, and David I. Laibson (2013). "Optimal Mortgage Refinancing: A Closed-Form Solution". In: *Journal of Money, Credit and Banking* 45, pp. 591–622.

Agarwal, Sumit, Richard J. Rosen, and Vincent Yao (2015). "Why Do Borrowers Make Mortgage Refinancing Mistakes?" In: *Management Science* 62, pp. 3494–3509.

Ameriks, John et al. (2020). "Older Americans Would Work Longer if Jobs Were Flexible". In: *American Economic Journal* 12, pp. 174–209.

Amromin, Gene, Neil Bhutta, and Benjamin J. Keys (2020). "Refinancing, Monetary Policy and the Credit Cycle". In: *Annual Review of Financial Economics* 12.

Beraja, Martin et al. (2019). "Regional Heterogeneity and the Refinancing Channel of Monetary Policy". In: *Quarterly Journal of Economics* 134, pp. 109–183.

Berger, David W. et al. (2021). "Mortgage Prepayment and Path-Dependent Effects of Monetary Policy". In: *American Economic Review* 111, pp. 2829–2878.

Bonhomme, Stephane and Elena Manresa (2015). "Grouped Patterns of Heterogeneity in Panel Data". In: *Econometrica* 83, pp. 1147–1184.

Christodoulou, Demetris and Vasilis Sarafidis (2017). "Regression Clustering for Panel-Data Models with fixed effects". In: *The Stata Journal* 17.2, pp. 314–329.

Defusco, Anthony A. and John Mondragon (2020). "No Job, No Money, No Refi: Frictions to Refinancing in a Recession". In: *Journal of Finance* 75.5.

Fuster, Andreas, Greg Kaplan, and Basit Zafar (2018). "What Would You Do with $500? Spending Responses to Gains, Losses, News and Loans". In: *Federal Reserve Bank of New York Staff Reports* 843.

Gerardi, Kristopher, Paul Willen, and David Zhang (2020). "Mortgage Prepayment, Race, and Monetary Policy". In: *Federal Reserve Bank of Boston Working Papers* 20-7.

Green, Richard K. and Michael LaCour-Little (2000). "Some Truths About Ostriches: Who Doesn't Prepay Their Mortgages and Why They Don't". In: *Journal of Housing Economics* 8, pp. 233–248.

Grundl, Serafin J. and You Suk Kim (2017). "Consumer Mistakes and Advertising: The Case of Mortgage Refinancing". In: *Finance and Economics Discussion Series from Board of Governors of the Federal Reserve* 67.

Heiss, Florian et al. (2021). "Inattention and Switching Costs as Sources of Inertia in Medicare Part D". In: *American Economic Review* 111, pp. 2737–2781.

Jappelli, Tullio and Luigi Pistaferri (2014). "Fiscal Policy and MPC Heterogeneity". In: *American Economic Journal* 6, pp. 107–136.

Keys, Benjamin J., Devin G. Pope, and Jaren C. Pope (2016). "Failure to Refinance". In: *Journal of Financial Economics* 122, pp. 482–499.

Lewis, Daniel J., Davide Melcangi, and Laura Pilossoph (2021). "Latent Heterogeneity in the Marginal Propensity to Consume". In: *Federal Reserve Bank of New York Staff Reports* 902.

McCartney, W. Ben and Avni Shah (2021). "Household Mortgage Refinancing Decisions are Neighbor Influenced". In: *FRB of Philadelphia Working Papers* 21-16.

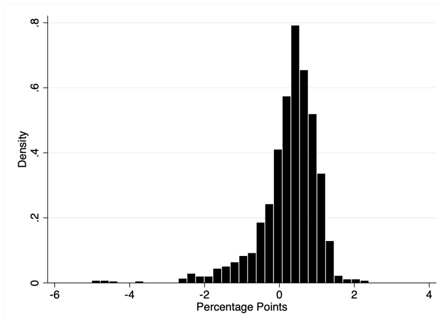
Parker, Jonathan A. et al. (2013). "Consumer Spending and the Economic Stimulus Payments of 2008". In: *American Economic Review* 103, pp. 2530–2553.

Sarafidis, Vasilis and Neville Weber (2015). "A Partially Heterogeneous Framework for Analyzing Panel Data". In: *Oxford Bulletin of Economics and Statistics* 77.

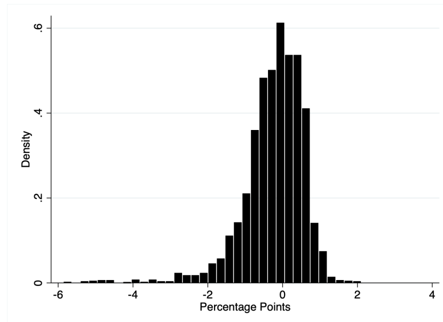
Tibshirani, Robert, Guenther Walther, and Trevor Hastie (2001). "Estimating the Number of Clusters in a Data Set via the Gap Statistic". In: *Journal of the Royal Statistical Society* 63, pp. 411–423.

Appendix

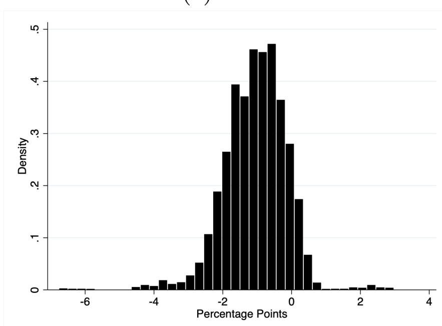
1 Rate Gap Over Time



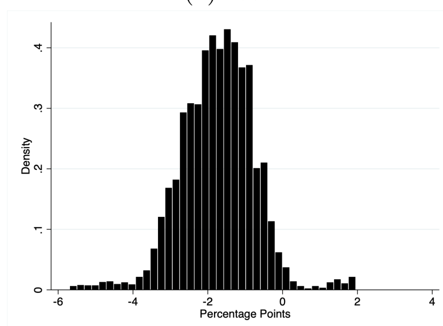
(a) 2006



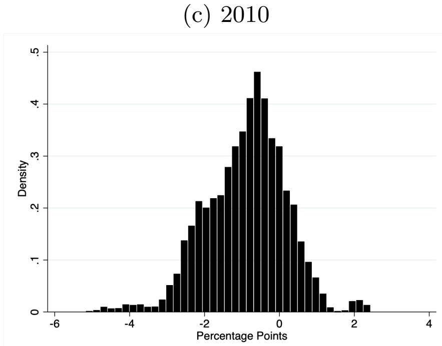
(b) 2008



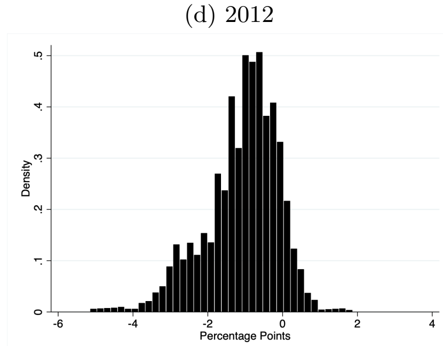
(c) 2010



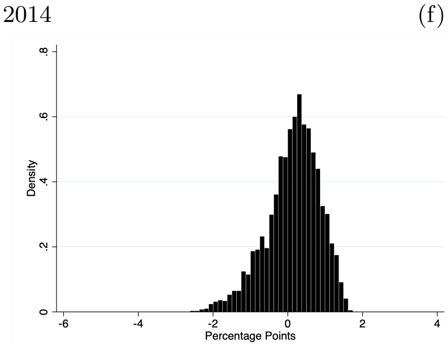
(d) 2012



(e) 2014



(f) 2016



(g) 2018

Figure 2: Distribution of Rate Gaps Over Time

2 Multinomial Logit

I regress group membership on the same array of observables to investigate joint significance. Table 8 shows the log odds of being in each group for six key observables: racial composition (represented as both the fraction of non-white residents and separately the fraction of Black and Asian residents), education, employment, household income, home value and credit score. I regard the estimates in this table as a useful measure of statistical significance and relative magnitude across groups. Estimates are relative to Group 4, which exhibits the highest APR and MPR across all groups. From Table 8, We see that many observables remain robust to the inclusion of other covariates.

Table 8: Multinomial Logit

	Group 1 (2)	Group 2 (3)	Group 3 (4)	Group 5 (5)	Group 6 (6)	Group 7 (7)	Group 8 (8)
Fraction Non-White	5.978***	5.213***	14.400***	10.301***	8.845***	7.782***	-1.273
	(1.287)	(1.259)	(1.282)	(1.279)	(1.276)	(1.266)	(1.353)
Fraction Black	-12.367***	-13.413***	-21.129***	-16.511***	-14.171***	-13.767***	-3.481**
	(1.402)	(1.378)	(1.407)	(1.395)	(1.394)	(1.382)	(1.461)
Fraction Asian	-13.912***	-12.314***	-22.972***	-23.336***	-24.070***	-17.661***	-10.737***
	(1.926)	(1.871)	(1.902)	(1.930)	(1.921)	(1.887)	(2.198)
Fraction College	-15.256***	-12.162***	-14.980***	-12.921***	-19.164***	-14.479***	-17.282***
	(1.002)	(0.979)	(0.999)	(1.000)	(0.988)	(0.983)	(1.059)
Fraction Employed	27.486***	23.592***	26.965***	27.616***	36.231***	27.421***	35.472***
	(1.818)	(1.792)	(1.849)	(1.816)	(1.813)	(1.797)	(1.865)
Median Household Income	0.013***	-0.009***	0.015***	0.001	0.014***	0.001	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Median Home Value	-0.016***	-0.003***	-0.002***	-0.011***	-0.005***	-0.010***	-0.039***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FICO Score at Origination	0.003***	0.000	0.005***	0.005***	0.003***	-0.001	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Type (APR, MPR)	Low, High	Low, Low	High, Low	Low, Low	High, High	Low, Low	High, High

Note: This table presents estimates of a multinomial logit regression of group membership on the same array of observables as in Table 5. All estimates are relative to Group 4 (omitted). (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

3 Refinance Survey

3.1 Recruitment Email

Dear Member:

Researchers at the Duke University Department of Economics have requested your input in support of an on-going research project at Duke. We are excited to share this opportunity with you.

You are invited to participate in a survey (optional) that will ask you a series of questions regarding your views and familiarity with refinancing. This optional 18-question survey will take approximately six minutes to complete. By taking the survey you consent to having your responses published, however your responses will only be reported in the aggregate.

Thank you for your consideration in support of research at Duke!

Click Here to Take the Survey (Button)

In accordance with Duke University Federal Credit Union's privacy policy we have not shared any personal member information.

3.2 Survey Questions

1. Before taking this survey, how familiar were you with refinancing?
    (a) Extremely familiar
    (b) Moderately familiar
    (c) Somewhat familiar
    (d) Not at all familiar
2. Do you know anyone who has considered refinancing their home?
    (a) I know many people who have considered refinancing their homes.
    (b) I know some people who have considered refinancing their homes.
    (c) I know a few people who have considered refinancing their homes.
    (d) I don't know anyone who has considered refinancing their home.
3. Do you currently have a mortgage?
    (a) Yes, I currently have a mortgage.
    (b) No, I do not currently have a mortgage.
4. Have you ever had a mortgage?
    (a) Yes, I have had a mortgage.
    (b) No, I have never had a mortgage.
5. Have you ever refinanced a mortgage?
    (a) Yes, I have refinanced a mortgage.
    (b) No, I have never refinanced a mortgage.
6. Do you know the interest rate that you pay on your primary home loan? If so, what is it?
    (a) Yes. The interest rate on my primary home loan is:
    (b) No, I don't know the interest rate that I pay on my primary home loan.

    Questions Asked to All Participants Who Have Refinanced:

7. After refinancing, how much did you save on your monthly mortgage payment?

8. Below are some common reasons why households choose to refinance. Please select all that apply to you.
   (a) To lower my monthly mortgage payment.
   (b) To extract equity (cash) from my home.
   (c) To change my loan terms.
   (d) Other
9. If you would like to explain any of your answers in more depth, please feel free to do so below.

Questions Asked to All Participants Who Have Not Refinanced:

10. Have you ever considered refinancing any mortgage?
    (a) Yes, I have considered refinancing any mortgage.
    (b) No, I have never considered refinancing any mortgage.
    (c) I did not know what refinancing was before this survey.
11. Below are some common reasons why households choose not to refinance their mortgages. Please select all that apply to you.
    (a) My credit score is too low.
    (b) I don't know what my credit score is.
    (c) I don't have the necessary documents.
    (d) I am unemployed.
    (e) I can't afford to pay the extra fees.
    (f) I don't understand how refinancing works.
    (g) I don't think that I would benefit from refinancing my home.
    (h) I don't trust financial institutions to have my best interest in mind.
    (i) I think that it is too much effort.
    (j) I think that it takes too much time.
    (k) My peers don't refinance their mortgages.
    (l) I have not had a mortgage for long enough to qualify for a refinance.
    (m) I am moving soon.

(n) Other

12. If you would like to explain any of your answers in more depth, please feel free to do so below.

13. What, if anything, would make you more likely to refinance your mortgage?

Demographic Questions Asked of All Participants.

14. What is your age?

    (a) 18-24

    (b) 25-34

    (c) 35-44

    (d) 45-54

    (e) 55-64

    (f) 65-74

    (g) 75 or older

15. What gender do you identify as?

    (a) Male

    (b) Female

    (c) Non-binary

    (d) Prefer not to say

16. How would you best describe yourself? Please check all that apply.

    (a) White

    (b) Black or African American

    (c) Asian

    (d) American Indian/Alaska Native/Native Hawaiian or Pacific Islander

    (e) Other

    (f) Prefer not to say

17. What is the highest degree or level of education that you have completed?

(a) Some high school

(b) High school

(c) Some college

(d) Bachelor's degree

(e) Master's degree

(f) PhD or higher

(g) Prefer not to say

18. What was your total household income before taxes in 2020?

    (a) Less than $10,000

    (b) $10,000-$19,999

    (c) $20,000-$29,999

    (d) $30,000-$39,999

    (e) $40,000-$49,999

    (f) $50,000-$59,999

    (g) $60,000-$69,999

    (h) $70,000-$79,999

    (i) $80,000-$89,999

    (j) $90,000-$99,999

    (k) $100,000-$150,000

    (l) More than $150,000

    (m) Prefer not to say

19. What is your current credit score?

    (a) 300-579

    (b) 580-669

    (c) 670-739

    (d) 740-799

    (e) 800-850

    (f) Don't know

    (g) Prefer not to say